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Stochastic Programming of Vehicle to Building Interactions with Uncertainty in PEVs Driving for a Medium Office Building

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***Abstract*— The large scale penetration of electric vehicles (EVs) will introduce technical challenges to the distribution grid, but also carries the potential for vehicle-to-grid services. Namely, if available in large enough numbers, EVs can be used as a distributed energy resource (DER) and their presence can influence optimal DER investment and scheduling decisions in microgrids. In this work, a novel EV fleet aggregator model is introduced in a stochastic formulation of DER-CAM [1], an optimization tool used to address DER investment and scheduling problems. This is used to assess the impact of EV interconnections on optimal DER solutions considering uncertainty in EV driving schedules. Optimization results indicate that EVs can have a significant impact on DER investments, particularly if considering short payback periods. Furthermore, results suggest that uncertainty in driving schedules carries little significance to total energy costs, which is corroborated by results obtained with the stochastic formulation of the problem.**

***Index Terms*— microgrids, uncertainty, electric vehicles, electric storage, distributed energy resources, driving patterns.**

I. Introduction

The definition of Distributed Energy Resources (DER) expands on the definition of Distributed Generation (DG) by including both storage and controllable loads. It carries all the potential benefits of DG, but also considers additional load shifting and demand response measures that add to the complexity of strategic DER investment and scheduling decisions in microgrids, particularly under uncertainty. New and emerging technologies add to this problem, and plug-in electric vehicles (EV) are a clear example. A large scale penetration of EVs in microgrids will introduce new technological challenges and add to electric loads, but will also carry a significant potential for ancillary services. Under this scenario EVs will be considered as a DER and must be considered in DER investment decisions.

Vehicle-to-grid interactions (V2G) is a relatively new concept and is based on the principle that if a significantly high number of EVs is available at the grid it will not only have an impact on the loads, but will also have the potential to be used as a DER. A common approach to the interface between the EVs and the grid is the use of Aggregators, so that the full V2G potential can be achieved and the EV fleet can be effectively integrated and managed [2]. The economic viability and business models of V2G technology have already been addressed [3], [4], and models have been presented regarding EV bidding and optimal charging strategies [5]. Some work has also been focused on the problem of optimally managing a microgrid including vehicle-to-grid interactions [6], [7], and in [8] a stochastic model was used to optimize the use of renewable sources to charge EVs. However, few studies address V2G benefits while analyzing DER investments at microgrids.

Some studies have addressed DER investment and scheduling problems: An MILP model, DER-CAM, is described in [1], dealing with optimal DER investment and introducing the impact of carbon taxation in optimal investment decisions. A similar model is introduced in [9], dealing with DER investments in Japan. In [10], DER-CAM is used to address the investment and planning decisions of DERs in the presence of EVs as a deterministic optimization problem, while the EV fleet Aggregator model considers only a single driving schedule for the entire fleet and defines a typical year by 3 typical days of hourly loads per month.

The work presented in this paper advances the state-of-the-art of DER investment and scheduling problems by adding to the work presented in [11]. This is accomplished by proposing a novel stochastic programming formulation of the problem with a new EV fleet aggregator model and considering uncertainty in driving schedules. An updated version of DER-CAM has been designed and is used for this purpose, where the typical year is defined using 7 typical days of hourly loads per month (a total of 84 typical days per year). The impact of EVs in DER investments is analyzed on a case study with technology costs and performance coefficients being forecasted for 2020, when it is expected that EVs will be widely available and V2G benefits within reach.

The remainder of this paper is organized as follows: Section II introduces briefly DER-CAM and its main versions and past applications. Section III describes the EV fleet aggregator model proposed in this work and Section IV introduces the stochastic formulation of DER-CAM. Section V introduces the data used in the case study, and the optimization runs and main results obtained. In Section VI, the main conclusions are presented.

II. DER-CAM

DER-CAM is a MILP model developed by the Lawrence Berkeley National Laboratory and used extensively to address the problem of optimally investing and scheduling DER under multiple settings. Its earliest development stages go back to

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2000 [12], and stable versions can be accessed freely by the general public using a web interface [13]. Along with HOMER [14], formerly developed by the National Renewable Energy Laboratory, it is one of the few optimization tools of its kind that is available for public use. It has been continuously improved to incorporate new technologies and features, and used in several peer-reviewed publications [1], [15–17]. Recently, it has also been updated to incorporate EVs [11]. The key inputs in DER-CAM are customer loads, market tariffs including electric and natural gas prices, techno-economic data of DG technologies including capital and operation and maintenance costs, electric efficiency, heat-to-power ratio, sprint capacity, maximum operating hours, among others. Key outputs include energy costs, the optimal installed onsite capacity and dispatch of selected technologies, and demand response measures.

Since the focus of this work is stochastic programming of the new aggregated EV interconnection model for the DER-CAM to consider uncertainty in driving schedules, only the most relevant mathematical models are presented and the full mathematical model implemented in DER-CAM can be found in [1], [15–17].

III. EV Fleet Aggregator Model

A new EV fleet model is proposed in this paper such that the EV fleet can be distributed between one of four states in each time step – at the microgrid, in traffic going home, in traffic to the microgrid, and at home – and all variables concerning EV operations are calculated explicitly in each time step, which also allows forcing continuity in the state of charge (SOC) in EVs between consecutive days.

Additionally, the following assumptions were considered in the new aggregator model:

- The non-dimensional time-dependent distribution of the EV fleet between different states is known;
- Electricity used for driving is not considered in microgrid energy costs;
- All cars charge at least enough electricity at home for an average daily roundtrip;
- Electricity meant only for driving can also be used while cars are at the microgrid, but if so, it must be recharged by the microgrid;
- When cars change state, the SOC of these cars is equal to the average SOC of cars in the departing state;
- If cars transition between "Home" and "Traffic to microgrid", the SOC of these cars is equal to the average SOC of cars at "Home", plus the amount required for a daily roundtrip;
- Electric vehicle charging and discharging strategies are defined by the microgrid cost minimization objective.

A schematic representation of the aggregator model introduced is shown in Fig. 1. It must be noted that the total EV fleet dimension is a decision variable, as well as the electricity stored in each state and time step, and the electricity inputs and outputs both at home and at the microgrid. Conversely, the share of cars in each state is known and given by a time-dependent discrete distribution, as well as the share of cars transitioning between two states. As total EV fleet capacity is determined, so are the electricity needs for driving.

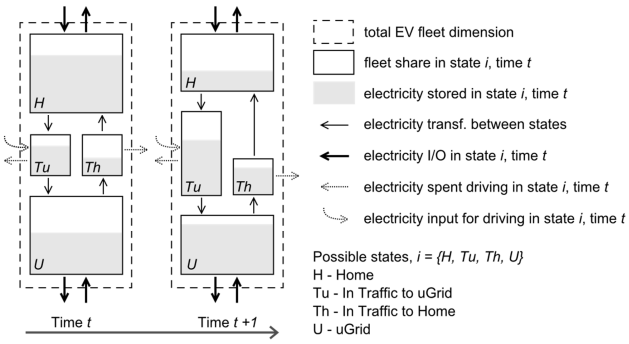

Fig. 1. Schematic diagram of EV aggregator model.

The electricity transferred between states is determined given total capacity and the SOC in each state and each time step.

A. Mathematical Formulation

The detailed EV fleet aggregator mathematical formulation is described as follows:

1) Indices

c : set of continuous generation technologies: photovoltaic panels (PV), solar thermal panels (ST), and absorption chillers (AS).

h : hour {1,2,...,24}

k : set of storage technologies: Electric Vehicles (EV), stationary storage (ES), and thermal storage (TH).

m: month {1,2,...,12}.

t : day of week {1,2,...7}.

ω : scenario {1,2,...,Ω}.

2) Fleet distribution parameters

$EVH_{\omega,m,t,h}$: share of total EV fleet that is at home in scenario ω, month m, day t, and during hour h.

$EVTU_{\omega,m,t,h}$: share of total EV fleet that is in traffic towards the microgrid in scenario ω, month m, day t, and during hour h.

$EVU_{\omega,m,t,h}$: share of total EV fleet that is at the micro-grid in scenario ω, month m, day t, and during hour h.

$EVTH_{\omega,m,t,h}$: share of total EV fleet that is in traffic towards home in scenario ω, month m, day t, and during hour h.

$EVT2H_{\omega,m,t,h}$: share of total EV fleet that arrived home from traffic in scenario ω, month m, day t, and during hour h.

$EVH2T_{\omega,m,t,h}$: share of total EV fleet that left home to traffic in scenario ω, month m, day t, and during hour h.

$EVT2U_{\omega,m,t,h}$: share of total EV fleet that arrived the micro-grid from traffic in scenario ω, month m, day t, and during hour h.

$EVU2T_{\omega,m,t,h}$: share of total EV fleet that left the micro-grid to traffic in scenario ω, month m, day t, and during hour h.

In order to ensure continuity the following conditions are imposed to the fleet distribution parameters:

$$EVH_{\omega,m,t,h} = EVH_{\omega,m,t,h-1} + EVT2H_{\omega,m,t,h} - EVH2T_{\omega,m,t,h}, \quad \forall\, \omega, m, t, h \tag{1}$$

$$EVTU_{\omega,m,t,h} = EVTU_{\omega,m,t,h-1} + EVH2T_{\omega,m,t,h} - EVT2U_{\omega,m,t,h}, \forall\, \omega, m, t, h \tag{2}$$

$$EVTH_{\omega,m,t,h} = EVTH_{\omega,m,t,h-1} + EVU2T_{\omega,m,t,h} - EVT2H_{\omega,m,t,h}, \forall\, \omega, m, t, h \tag{3}$$

$$EVU_{\omega,m,t,h} = EVU_{\omega,m,t,h-1} + EVT2U_{\omega,m,t,h} - EVU2T_{\omega,m,t,h}, \quad \forall\, \omega, m, t, h \tag{4}$$

These equations state that in any given scenario, month and day, the share of the total EV fleet in any state and given hour is equal to the share of that state in the previous hour, added

with the share of cars that arrived to that state and subtracted with the share of cars that left it during that hour.

3) Storage parameters

$\mathrm{SCRate_k}$ maximum charge rate of storage technology k.
$\mathrm{SDCRate_k}$ maximum discharge rate of storage technology k.
$\overline{\mathrm{SOC_k}}$ maximum state of charge of storage technology k.
$\underline{\mathrm{SOC_k}}$ minimum state of charge of storage technology k.
φ_k losses self-discharge in storage technology k.
EVBat average storage capacity per car (kWh).
EVDC electricity consumed for driving per car and per hour (kWh).
TotPS total available parking space for EVs (m2).
PSCar parking space required per EV (m2).

4) Decision Variables

$cap_{(c,k)}$: installed capacity of continuous generation technology c or storage technology k (kW or kWh).
$esevh_{\omega,m,t,h}$: electricity stored in EVs at home in scenario ω, month m, day t, and during hour h (kWh).
$esevtu_{\omega,m,t,h}$: electricity stored in EVs in traffic towards the microgrid in scenario ω, month m, day t, and during hour h (kWh).
$esevth_{\omega,m,t,h}$: electricity stored in EVs in traffic towards home in scenario ω, month m, day t, and during hour h (kWh).
$esevu_{\omega,m,t,h}$: electricity stored in EVs at microgrid in scenario ω, month m, day t, and during hour h (kWh).
$eievh_{\omega,m,t,h}$: electricity input to EVs at home in scenario ω, month m, day t, and during hour h (kWh).
$eoevh_{\omega,m,t,h}$: electricity output from EVs at home in scenario ω, month m, day t, and during hour h (kWh).
$SInput_{\omega,k,m,t,h}$: energy input from the microgrid in scenario ω, to storage technology k, , month m, day t, and during hour h (kWh).
$SOutput_{\omega,k,m,t,h,u}$: energy output to the microgrid in scenario ω, from storage technology k, month m, day t, and during hour h for end use u (kWh).
$ebioevh_{\omega,m,t,h}$: binary charge/discharge decision for EVs at home in scenario ω, month m, day t, and hour h.
$ebiou_{\omega,k,m,t,h}$: binary charge/discharge decision at the microgrid in scenario ω, storage technology k, month m, day t, and during hour h.

B. EV Aggregator Constraints

The mathematical model of an EV aggregator is developed as the following set of constraints:

$$esevh_{\omega,\mathrm{m,t,h}} = \left(esevh_{\omega,\mathrm{m,t,h-1}} \cdot \left(1 - \frac{\mathrm{EVH2T_{\omega,m,t,h}}}{\mathrm{EVH_{\omega,m,t,h-1}}}\right) + esevth_{\omega,\mathrm{m,t,h-1}} \cdot \frac{\mathrm{EVT2H_{\omega,m,t,h}}}{\mathrm{EVTH_{\omega,m,t,h-1}}}\right) \cdot (1-\varphi_\mathrm{k}) + eievh_{\omega,\mathrm{m,t,h}} - eoevh_{\omega,\mathrm{m,t,h}} \quad (5)$$

$$esevth_{\omega,\mathrm{m,t,h}} = \left(esevth_{\omega,\mathrm{m,t,h-1}} \cdot \left(1 - \frac{\mathrm{EVT2H_{\omega,m,t,h}}}{\mathrm{EVTH_{\omega,m,t,h-1}}}\right) + esevu_{\omega,\mathrm{m,t,h-1}} \cdot \frac{\mathrm{EVU2T_{\omega,m,t,h}}}{\mathrm{EVU_{\omega,m,t,h-1}}}\right) \cdot (1-\varphi_\mathrm{k}) - \mathrm{EVT2H_{\omega,m,t,h}} \cdot \frac{cap_\mathrm{k}}{\mathrm{EVBat}} \cdot \mathrm{EVDC} \quad (6)$$

$$esevtu_{\omega,\mathrm{m,t,h}} = \left(esevtu_{\omega,\mathrm{m,t,h-1}} \cdot \left(1 - \frac{\mathrm{EVT2U_{\omega,m,t,h}}}{\mathrm{EVTU_{\omega,m,t,h-1}}}\right) + esevh_{\omega,\mathrm{m,t,h-1}} \cdot \frac{\mathrm{EVH2T_{\omega,m,t,h}}}{\mathrm{EVH_{\omega,m,t,h-1}}}\right) \cdot (1-\varphi_\mathrm{k}) + \left(\sum_\mathrm{h}\left(\mathrm{EVTU_{\omega,m,t,h}} + \mathrm{EVTH_{\omega,m,t,h}}\right) \cdot \frac{\mathrm{EVH2T_{\omega,m,t,h}}}{\sum_\mathrm{h} \mathrm{EVH2T_{\omega,m,t,h}}} - \mathrm{EVT2U_{\omega,m,t,h}}\right) \cdot \frac{cap_\mathrm{k}}{\mathrm{EVBat}} \cdot \mathrm{EVDC} \quad (7)$$

$$esevu_{\omega,\mathrm{m,t,h}} = \left(esevu_{\omega,\mathrm{m,t,h-1}} \cdot \left(1 - \frac{\mathrm{EVU2T_{\omega,m,t,h}}}{\mathrm{EVU_{\omega,m,t,h-1}}}\right) + esevtu_{\omega,\mathrm{m,t,h-1}} \cdot \frac{\mathrm{EVT2U_{m,t,h}}}{\mathrm{EVTU_{m,t,h-1}}}\right) \cdot (1-\varphi_\mathrm{k}) + SInput_{\omega,\mathrm{k,m,t,h}} - SOutput_{\omega,\mathrm{k,m,t,h}} \quad (8)$$

In this model, constraints (5)-(8) describe how energy is transferred between different states, including all charging and discharging decisions both at home and at the microgrid. For instance, Constraint (5) states that the in each scenario, month and day, the electricity in cars parked at home in any given hour is equal to the electricity in cars parked at home in the previous hour, minus the electricity in cars that went into traffic, plus the electricity in cars that arrived from traffic, plus the electricity from charging at home, minus the electricity from discharging at home during that hour. Constraints (6) and (7) are similar, but also include energy needs for driving.

$$\mathrm{EVH_{\omega,m,t,h}} \cdot \underline{\mathrm{SOC_k}} \cdot cap_\mathrm{k} \le esevh_{\omega,\mathrm{m,t,h}} \le \mathrm{EVH_{\omega,m,t,h}} \cdot \overline{\mathrm{SOC_k}} \cdot cap_\mathrm{k} \quad (9)$$

$$\mathrm{EVTU_{\omega,m,t,h}} \cdot \underline{\mathrm{SOC_k}} \cdot cap_\mathrm{k} \le esevtu_{\omega,\mathrm{m,t,h}} \le \mathrm{EVTU_{\omega,m,t,h}} \cdot \overline{\mathrm{SOC_k}} \cdot cap_\mathrm{k} \quad (10)$$

$$\mathrm{EVTH_{\omega,m,t,h}} \cdot \underline{\mathrm{SOC_k}} \cdot \mathrm{cap_k} \le \mathrm{esevth_{\omega,m,t,h}} \le \mathrm{EVTH_{\omega,m,t,h}} \cdot \overline{\mathrm{SOC_k}} \cdot \mathrm{cap_k} \quad (11)$$

$$\mathrm{EVU_{\omega,m,t,h}} \cdot \underline{\mathrm{SOC_k}} \cdot \mathrm{cap_k} \le \mathrm{esevu_{\omega,m,t,h}} \le \mathrm{EVU_{\omega,m,t,h}} \cdot \overline{\mathrm{SOC_k}} \cdot \mathrm{cap_k} \quad (12)$$

$$eievh_{\omega,\mathrm{m,t,h}} \le \mathrm{EVH_{\omega,m,t,h}} \cdot cap_\mathrm{k} \cdot \mathrm{SCRate_k} \quad (13)$$

$$eoevh_{\omega,\mathrm{m,t,h}} \le \mathrm{EVH_{\omega,m,t,h}} \cdot cap_\mathrm{k} \cdot \mathrm{SDCRate_k} \quad (14)$$

$$SInput_{\mathrm{k},\omega,\mathrm{m,t,h}} \le \mathrm{EVU_{\omega,m,t,h}} \cdot cap_\mathrm{k} \cdot \mathrm{SCRate_k} \quad (15)$$

$$\sum_\mathrm{u} SOutput_{\mathrm{k},\omega,\mathrm{m,t,h,u}} \le \mathrm{EVU_{\omega,m,t,h}} \cdot cap_\mathrm{k} \cdot \mathrm{SDCRate_k} \quad (16)$$

$$eievh_{\omega,\mathrm{m,t,h}} \le ebioevh_{\omega,\mathrm{m,t,h}} \cdot \mathbf{M} \quad (17)$$

$$eoevh_{\omega,\mathrm{m,t,h}} \le \left(1 - ebioevh_{\omega,\mathrm{m,t,h}}\right) \cdot \mathbf{M} \quad (18)$$

$$SInput_{\omega,\mathrm{k,m,t,h}} \le ebiou_{\omega,\mathrm{k,m,t,h}} \cdot \mathbf{M} \quad (19)$$

$$SOutput_{\omega,\mathrm{k,m,t,h}} \le \left(1 - ebiou_{\omega,\mathrm{k,m,t,h}}\right) \cdot \mathbf{M} \quad (20)$$

$$Cap_\mathrm{k} \le \frac{\mathrm{TotPS}}{\mathrm{PSCar}} \cdot \mathrm{EVBat} \ : \mathrm{k} = \{\mathrm{EV}\} \quad (21)$$

The maximum and minimum state of charge conditions are imposed by Eqs. (9)-(12), while Eqs. (13)-(16) set the maximum and minimum charge and discharge rates. Eqs. (17)-(20) ensure that charging and discharging cannot occur simultaneously, either at home or at the microgrid using binary variables and an arbitrary large quantity, **M**. Finally, Eq. (21) sets the maximum EV capacity according to the available parking space

IV. Stochastic Formulation

To date, only deterministic methods had been implemented in the DER-CAM. In this work, a stochastic formulation was implemented, already taking into account the EV fleet aggregator model described in the previous section. The

TABLE I - STORAGE PARAMETERS (DIMENSIONLESS)

	stationary electric storage	EV batteries
charging efficiency	0.90	0.90
discharging efficiency	0.90	0.90
self-discharge per hour	0.001	0.001
maximum charge rate	0.30	0.45
maximum discharge rate	0.30	0.45
minimum state of charge	0.30	0.20

TABLE II - EV PARAMETERS

Average battery size (kWh)	23.75
Battery replacement cost in 2020 ($/kWh)	200
Hourly driving consumption (kWh)	4.2
Infrastructure investment cost per car ($)	1000
Total parking space at microgrid (m^2)	16200
Parking space per car (m^2)	15

nomenclature used follows previous descriptions of the DER-CAM formulation [1]. Given the nature of DER-CAM, the stochastic formulation implemented and presented here is valid for the full economic objective function of the model, although the actual formulation and model options are adapted to each case study. For instance, in the work presented here no electricity sales were considered, thus the corresponding equations and variables were disabled or forced to zero.

The generic mathematical formulation of the two-stage stochastic DER-CAM is as follows:

$$\begin{aligned} \min \quad & c'x + \sum_{\omega=1}^{\Omega} \pi_\omega q_\omega{}' y_\omega \\ \text{s.t.} \quad & \sum_j a_{ij} x_j \le b_i \\ & \sum_k V_{k\omega} x_k + \sum_k W_{k\omega} y_{\omega s} \le h_\omega \quad \omega \in \{1,2,\ldots,\Omega\} \end{aligned} \tag{22}$$

where the economic objective function minimize total expected energy costs, consisting of the first and second stage problem objectives. The first-stage objective function, $c'x$, includes annualized DER investment costs. The second stage objective, $\sum_{\omega=1}^{\Omega} \pi_\omega q_\omega{}' y_\omega$, consists of facilities and customer charges, monthly demand charges, coincident demand charges, energy charges inclusive of carbon taxation, demand response measures and electricity sales in all scenarios. In addition, on-site generation fuel and O&M costs, carbon taxation on on-site generation, and natural gas used to meet heating loads are included in the second stage objective function. The investment variables, such as the type and size of adapted technologies, are the first stage decision variables. Daily operational variables of the selected technologies are the second stage variables of the two-stage stochastic problem.

V. CASE STUDIES

A. Input Data

The EV fleet Aggregator and stochastic implementation of DER-CAM introduced in this work has been tested by using detailed energy simulation loads of a medium office building located in San Francisco, as described in the California End-Use Survey (CEUS) database. The set of DER technologies considered in this study includes internal combustion engines (ICE), micro turbine (MT), gas turbine (GT), fuel cells (FC), heat exchangers (HX), absorption chillers (AC), stationary electricity storage (ES), solar PV, solar thermal panels (ST), and EVs. The costs and performance indicators of the DER technologies considered in this work can be found in [1], [15–17]. EVs and storage parameters are presented in Table I and Table II. The electricity tariff considered in this work is E-19 TOU (Time-of-use) tariff applied in the Pacific Gas & Electric

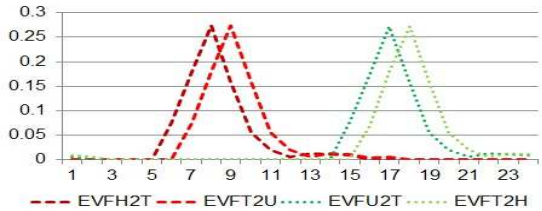

Fig. 2. EVs arrival and departure distributions.

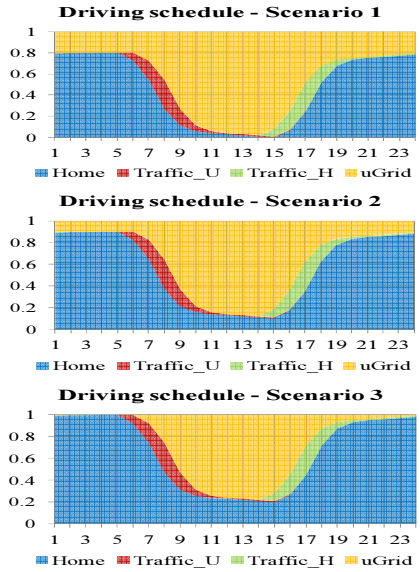

Fig. 3. Driving schedule scenarios.

service territory for buildings with electric peak loads over 200 kW and less than 499 kW [18].

B. Driving Schedules

The driving schedules used in this work were obtained from a 2009 US Commuting Survey [19]. This survey contains a detailed distribution of the departure time of employees commuting to work in the morning and back in the evening. In this work, it was assumed that the average travel time would be 1 h. In addition, it was assumed that the average time spent at the microgrid site was 8 h and that the departure distribution on the way back home was the same as the departure distribution going to work. The resulting fleet departure distribution is illustrated in Fig. 2.

Considering this departure distribution, (1)-(4) were solved to obtain the complete fleet distribution schedule used in this work. Three driving schedules were obtained solving these equations while maximizing the number of cars at home, maximizing the number of cars at the microgrid and calculating an average of the later. These driving schedules correspond to Scenarios 1, 3 and 2, respectively, and are presented in Fig. 3.

C. Simulation Results

The model presented in this paper was run using 4 parallel CPU threads on a 256 GB RAM server running GAMS 23.0.2 and CPLEX 11.2.1. Table III presents a summary of the simulation case studies presented here, and the key investment results obtained in the optimization runs are shown in Table IV. By inclusion of EVs in the set of available technologies, the model selects EVs which results in reductions in total energy costs and an increase in CO_2 emissions as compared to

TABLE III - KEY MODEL OPTIONS

Case Refs.	Description	DER Investment	EV Investment	EV Schedule	Payback Period (yr)
BAU	Business as usual	N	N	-	
NOEVP12	Invest No EV	Y	N	-	12
EVS1P12	Allow EVs S1	Y	Y	S1	12
EVS2P12	Allow EVs S2	Y	Y	S2	12
EVS3P12	Allow EVs S3	Y	Y	S3	12
EVSTP12	Allow EVs Stoch.	Y	Y	S1, S2, S3	12
EVSTP5	Allow EVs Stoch.	Y	Y	S1, S2, S3	5

TABLE IV - INVESTMENT RESULTS. 5YR PAYBACK AS CONSTRAINT.

Case Refs.	Optimality gap (%)	Total Energy Costs (k$)	Total CO2 (t CO2)	Optimal Capacity (kW)				
				PV	ST	ICE /HX	ES	EV
BAU	0	281,286	1,017,475	-	-	-	-	-
NOEVP12	0.091	269,530	737,856	189.9	-	60	-	-
EVS1P12	0.029	264,135	769,530	191.1	-	60	-	2,804
EVS2P12	0.057	265,257	758,197	192.3	-	60	-	2,005
EVS3P12	0.062	266,229	754,716	188.4	-	60	-	1,463
EVSTP12	1.087	266,270	823,138	201,1	83,7	-	-	2423
EVSTP5	0	269,293	1,053,325	-	50.9	-	-	3,578

the no EVs case, resulting from charging and discharging loses and the marginal CO_2 emissions during preferential charging hours, as presented in Fig. 4. Observe that the optimal mix of the adapted technologies obtained from solving the problem for each scenario individually is different from the ones obtained from the stochastic modeling formulation. Using the stochastic model for all the scenarios together promotes, in addition to the investment in EV charging stations, the selection of solar thermal and larger PV generation compared to the investment in ICE/EX with smaller PV generation for solving the scenarios independently. Notice that in the 5yr payback case the maximum possible EVs capacity is selected while in the 12yr payback this is not the case. Worthy to mention that because of the lower capital costs of investing in EVs for the microgrid, EV storage is used rather than ES.

The dispatch of the microgrid components for a summer week is shown in Fig. 5. Notice the potential of EVs for V2G services by allowing effective peak shaving by charging the cars at home and using the stored electricity at the microgrid, as shown in Fig. 6.

In general, the results suggest that in a high payback scenario, EVs show a lower impact on the total energy costs and DER investment decisions, as other technologies gain a higher weight. Also, considering uncertainty in EV driving schedules has little impact on total energy costs, which can result from the flexibility provided both by the large amount of EV capacity and the additional installation of local generation (EPVI = $1063 in 12 year paybacks).

VI. CONCLUSIONS

Optimal sizing and scheduling of DER capacity at a given site, considering the potential effect of electric vehicles and uncertainty in driving schedules were investigated. A novel EV fleet aggregator model was introduced and stochastic formulation was added to DER-CAM, a widely used deterministic model in DER sizing and scheduling problems. The presented aggregator model presented is based on a time-dependent fleet distribution that considers four different fleet

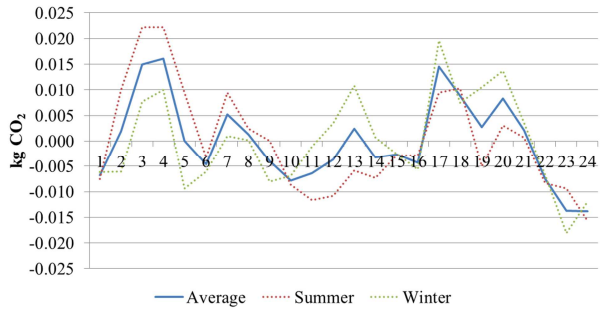

Fig. 4. Deviation of marginal macrogrid CO_2 levels from monthly average.

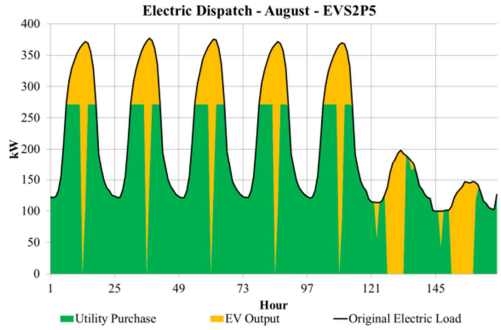

Fig. 5. Microgrid electric dispatch for August.

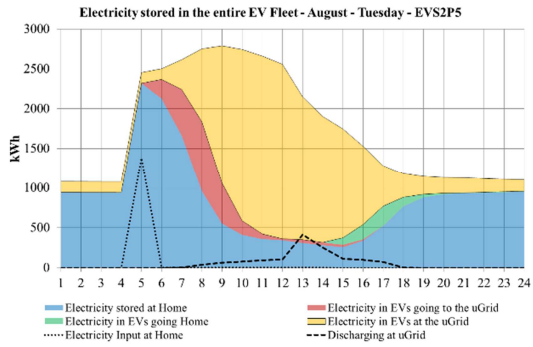

Fig. 6. Electricity stored in the entire EV fleet. Tuesday in August.

states and transitions between them. The model is then used to analyze the case study of a medium office building located in San Francisco, and real driving departure data are used to analyze the impact of EV driving schedule uncertainty in the DER investment decision.

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