This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TIA.2019.2929711, IEEE Transactions on Industry Applications

Coordinated Control of PEV and PV-based Storages in Residential System under Generation and Load Uncertainties

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***Abstract*—Energy storage deployment in residential and commercial applications is an attractive proposition for ensuring proper utilization of solar photovoltaic (PV) power generation. Energy storage can be controlled and coordinated with PV generation to satisfy electricity demand and minimize electricity purchases from the grid. For optimal energy management, PV generation and load demand uncertainties need to be considered when designing a control method for the PV-based storage system. Another resource available at the residential level is the plug-in electric vehicle (PEV) which also has bi-directional power flow capability. The charging and discharging routines of the PEV can be controlled to help reduce the energy drawn from the power grid during peak hours. In this paper, a method of coordinated optimal control between PV-based storage and PEV storage is proposed considering the stochastic nature of solar PV generation and load demand. The stochastic dual dynamic programming (SDDP) algorithm is employed to optimize the charge/discharge profiles of PV-based storage and PEV storage to minimize the daily household electricity purchase cost from the grid. Simulation analysis shows the advantage of the coordinated control compared to other control strategies.**

***Index Terms*—Control Strategy, Energy Storage, Plug-in Electric Vehicle, Solar Generation, Stochastic Programming.**

NOMENCLATURE

Indices

$\omega_{L,t}$	Generated scenario for load
ω_t	Generated scenario for solar generation
t	Index for time

Sets

$\Omega_{L,t}$	Set of generated scenario for load
$\Omega_{PV,t}$	Set of generated scenario for solar generation

Parameters

Δt	Time interval (min)
η_{PEV}	PEV storage charger efficiency in (%)
η_{PV}	PV-based storage charger efficiency in (%)
C_t	Time of use rate at time period t in ($/kWh)
$C_t^{off\_peak}$	Time of use rate during off peak in ($/kWh)
$C_t^{partial\_peak}$	Time of use rate during partial peak in ($/kWh)
k, C_d	Penalty factors
$P_c^{PEV\_max}$	Maximum PEV storage charging power in (kW)
$P_c^{PEV\_min}$	Minimum PEV storage charging power in (kW)
$P_c^{PV\_max}$	Maximum PV-based storage charging power in (kW)
$P_c^{PV\_min}$	Minimum PV-based energy storage charging power in (kW)
$P_d^{PEV\_max}$	Maximum PEV storage discharging power in (kW)
$P_d^{PEV\_min}$	Minimum PEV storage discharging power in (kW)
$P_d^{PV\_max}$	Maximum PEV storage discharging power in (kW)
$P_d^{PV\_min}$	Minimum PV-based energy storage discharging power in (kW)
$P_{L,t}$	Load demand at time period t (kW)
$P_{PV,t}$	Solar generation at time period t (kW)
Q_{PEV}	PEV storage capacity in (kWh)
Q_{PV}	PV-based energy storage capacity in (kWh)
SOC_{max}^{PEV}	Maximum PEV storage state of charge in (%)
SOC_{max}^{PV}	Maximum PV-based energy storage state of charge in (%)
SOC_{min}^{PEV}	Minimum PEV storage state of charge in (%)
SOC_{min}^{PV}	Minimum PV-based energy storage state of charge in (%)
$SOC_{t,leave}^{PEV}$	Leaving PEV storage state of charge in (%)
$SOC_{t,tar}^{PEV}$	Target PEV storage state of charge in (%)
T	Total Time period in (min)

Decision Variables

$P_{c,t}^{PEV}$	PEV storage charging power at time period t in (kW)
$P_{c,t}^{PV}$	PV-based energy storage charging power of at time period t in (kW)
$P_{d,t}^{PEV}$	PEV storage discharging power at time period t in (kW)
$P_{d,t}^{PV}$	PV-based energy storage discharging power of at time period t in (kW)
$P_{def,t}$	Deferred solar energy at time period t (kW)
$P_{g,t}$	Load demand from grid at time period t (kW)
SOC_t^{PEV}	PEV storage state of charge at time period t in (%)
SOC_t^{PV}	PV-based energy storage state of charge at time period t in (%)
x_t	Decision vector at time period t

Functions

$\mathbb{E}_{b_{t+1}\|b_t} h_{t+1}(x_t, b_{t+1})$	Expected cost function of time period $t+1$

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$\vert . \vert$	Represents the cardinality of a set, i.e. number of elements in a set
$h_{t+1}(.)$	Recursive function

I. Introduction

THE popularity of clean and renewable energy sources is increasing around the world due to the reductions in technology investment costs and the escalating goals of countries to implement sustainable standards in power and energy systems. As comparatively lower cost and environment friendly resources are being available, the deployment of renewable technologies are increasing in power systems. Among all the renewable resources, solar photovoltaic (PV) generation can be considered as a technology breakthrough for power generation at the residential level as it is easily accessible and is of moderate to low costs. According to an NREL study, rooftop solar could produce almost 40% of our electricity using the average efficiency of solar panels installed in 2015; in such situation, it would be possible to generate approximately 1,400 TWh of electricity each year and two-thirds of this amount would come from small residential buildings [1]. Figure 1 shows the change of rooftop solar potential in U.S.A from 2006 to 2016.

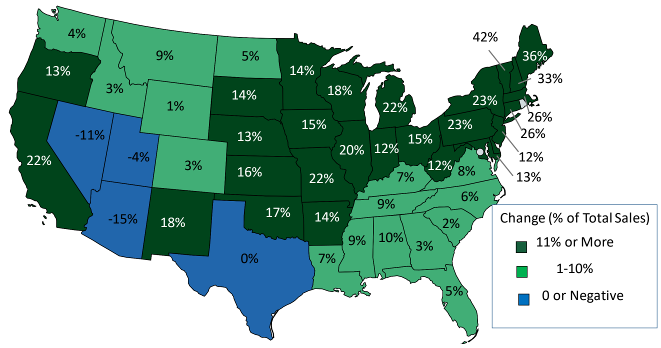

Figure 1: Rooftop solar potential change from the year 2008 – 2016 [1].

Along with solar PV generation, energy storage technologies are sufficiently developed to be used in conjunction with solar panels to store excess PV generation and use it during periods when solar generation is not available to improve the utilization and robustness of the system. According to the Energy Storage Association, 36 MWh of behind the meter residential storage were installed in the first quarter of 2018 in the US [2]. This is a dramatic increase from 50% from the year 2017. California and Hawaii together constitute 74% of residential storage deployments in 2018 which can be attributed to the change in states' net metering rules [2]. The dispatch between the PV panel and storage can be controlled considering the household electricity demand profile and time of use rate (ToU) of electricity to ensure economic benefit to the users [3]. Other dispatch objectives such as power balance, peak shaving/load shifting, and back-feeding power reduction [4]–[6] were considered for behind the meter applications for the PV-storage hybrid system.

Similar to solar PV generation and battery storage systems, plug-in electric vehicles (PEVs) are receiving more attention these days for reducing vehicle CO2 emissions [7]. Moreover, PEVs are likely to become cost-competitive compared with vehicles that rely on combustion engines in the near future [8]. California Energy Commission reported that the number of users of PEVs will reach approximately 1.3 million by 2025 only in California, and the annual sale of PEVs in 2025 will increase by more than 7% compared to 2017 [9]. Navigant Research reported that California, New York, Washington, and Florida will lead the way in PEV sales in the years ahead [10]. However, uncoordinated PEV charging at the residential level will significantly increase the peak load, what will likely affect electricity distribution infrastructures [11]. The aggregated PEV charging load at the residential level is expected to reach peaks levels of about 800MW in the evening by the year 2025 [12]. Therefore, recent research has focused on the approaches for PEV integration into the grid [13]. As PEVs have bi-directional power flow capabilities, the charging and discharging patterns of PEVs can be controlled [14]. However, controlling PEV from grid level requires an effective communication system, and there are also privacy and PEV owner preference concerns. Considering these issues, PEV charge/discharge scheduling from the residential level was proposed to reduce electricity purchase costs in [15].

The above discussion and trends serve as the motivation to develop energy management control methods for simultaneous deployment of PV-based storage and PEV at the residential level in near future. The two types of storage devices can be utilized using a coordinated control algorithm to maximize the economic benefits of a residential customer. From the customers' perspective, when these two storages are used in a household, they can be coordinated optimally to enhance the proper utilization of the system resources. Coordinated control of PEV and PV-panel energy storage has been considered in prior literature for various objectives such as to achieve power balance, load shifting, electricity cost reduction, and peak shaving [16]–[18]. These works did not consider the uncertainties of PV generation and load profiles, and furthermore, in some cases considered power curtailment which is undesirable considering the investment made on solar PV units. There is considerable uncertainty in solar and wind power generation due to changes in weather, and also, in homeowners electricity usage patterns [19]. In [20], non-Gaussian uncertainties of wind power and the PEV were considered within a hierarchical stochastic control scheme for the coordination of PEV charging and wind power generation in a microgrid to achieve the power balance between supply and demand; however, economic benefits were not considered in this work. Uncertainties in PV generation and electricity demand were considered in earlier research by the authors, but those were evaluated separately and not for a coordinated control scheme [21], [22]. Wu et al. considered uncertainty of PEV mobility for a stochastic control method to utilize generated solar energy but did not incorporate any PV-based storage [23]. Kavousi et al. showed that the uncertain variations of residential load demand and solar PV generation due to weather changes are correlated [24]. Therefore, it is

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necessary to consider the stochasticity of both PV generation and load demand as well as the correlation structure between them for any optimal energy management control framework. Furthermore, the coordination between the PV-based storage and PEV storage control is also necessary if both are available in a household to improve the solar generation utilization and reduce the net electricity purchase costs. The two storages are preferred to be controlled at the residential level to avoid privacy and ownership preference issues while simultaneously minimizing the communications requirements.

In this paper, a novel coordinated control strategy between solar PV generation with an energy storage device and PEV is presented. For a more realistic representation of the proposed decision-making framework, the approach is modelled considering the uncertainties in solar generation and household electricity demand [25]. The reminder of this paper is segregated as follows: The system representation is discussed in Section II. Section III describes the proposed methodology that includes the scenario generation procedure considering the correlation between load demand and solar production using Cholesky factorization [26]. The optimization model formulation for the coordinated system, and the stochastic dual dynamic programming (SDDP) algorithm applied to solve the model and define the control strategies for the system in the context of stochastic PV generation and household electricity demand are also presented in Section III. The comparisons between coordinated and other control methods are given in Section IV based on simulation results. Section V presents the summary and conclusions of this paper.

II. System Representation

A household system consisting of a PV panel-storage and PEV is shown in Figure 2. The PV panel delivers energy to the household and also to the energy storage device through a DC bus and AC-DC converter. Energy storage is connected to the same DC bus through a bidirectional DC-DC converter. PEV is connected to the household with another DC bus through a bidirectional converter. DC-AC inverters feed power to the household from the DC bus. In this configuration, it is assumed that PV-based energy storage and the PEV can only deliver power to the household. We assume that the PV panel and the energy storage devices do not deliver power to the grid, although this reverse power flow feature can be added in the controller for systems where it is desirable. The household load and PEV can receive power from the grid, the PV panel and the energy storage device. PV panel, storage and PEV can communicates to the controller through a communication network. The controller sends the charge/discharge command to control the energy storage.

III. Proposed Methodology

A. Scenario generation

To enhance the decision-making capabilities of an optimization model to be developed for the problem at hand, it is key to properly model uncertainties in solar generation and load demand and consider them when attempting to solve the storage scheduling problem. In this work, we choose

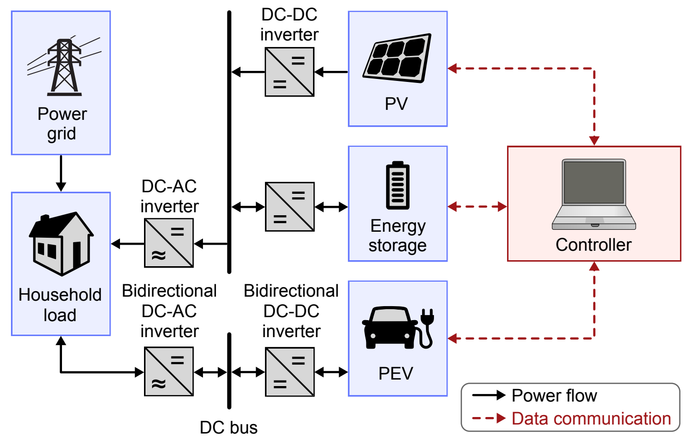

Figure 2: PV-storage hybrid unit and a connected PEV in a household system.

to model the future uncertainties by developing a scenario tree to represent possible events for the random parameters. PV generation and household electricity demand are sampled from a probability distribution in order to construct a finite scenario tree. In this process, no previous time dependency is considered to represent future uncertainty associated with scenario realizations.

Generally, outdoor temperature change leads to variations in the intensity of solar generation as well as changes in electricity demand patterns. For example, during a typical day in the summer, it is likely that the household electricity needs will be higher due to the cooling demand; on the other hand, solar PV production will be higher due to more intensity of the sunlight and more hours of sunshine. This requires a correlation structure to be considered between solar PV generation and load demand to represent possible future scenarios. Neglecting correlation between solar PV generation and load demand in the scenario generation procedure may lead to a scenario of lower load demand with higher solar generation.

We considered historical and forecasted data for PV generation and household electricity demand for 24-hour periods. To deal with the correlation, scenarios are generated for solar production and electricity demand independently sampling from normal distributions $\mathcal{N}[\mu, \sigma^2]$ and then passing the correlation structure through Cholesky decomposition. Following a similar notation from [26], suppose the number of stages is T and n is the number of uncertain parameters (in our case, $n = 2$). Let X be a matrix $(T \times n)$ with independent distributed draws from a normal distribution $\mathcal{N}[0, 1]$ and let R be the load and PV generation correlation matrix. The Cholesky decomposition of R is a lower triangular matrix L such that:

$$R = LL' \tag{1}$$

Now we can define Y such that:

$$Y = LX \tag{2}$$

where Y will then be a matrix with correlated draws. Therefore, Y will correspond to draws from $\mathcal{N}[0, \Sigma]$. The original

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draws are from a $\mathcal{N}[0,1]$, $\sigma = 1$ and the covariance matrix $\Sigma = R$. If we want to use correlated draws for solar PV generation and electricity demand, given by $\mathcal{N}_{t,i}[\mu_i, \sigma_i^2]$ where $i = 1, 2$ at a particular time stage t, we can multiply the draws from column i of Y by σ_i and sum the mean μ_i as similarly denoted in (3). For example, if $y_{t,i}$ is an element of the matrix Y corresponding to the i-th draw, then

$$\hat{y_{t,i}} = \mu_i + y_{t,i}\sigma_i \tag{3}$$

will be a draw from $\mathcal{N}_{t,i}$ $[\mu_i, \sigma_i^2]$. By following this procedure it is possible to generate scenarios to jointly represent our random parameters taking into account the correlation effects among them. It is to be noted that forecasted PV generation will not be available during the night. Thus during the night period, the generated PV profiles are zero and random for the load demand which will be generated from $\mathcal{N}[0,1]$.

B. Mathematical Model Formulation

Cost minimization of a household with optimal operation of energy storage devices integrated with PV and PEV in a system can significantly benefit a customer. In this study, a one-day cycle from 0hr to 24hr with a 15-minute resolution is considered. The total 24hr is divided into T time periods based on a resolution Δt. Let C_t be the ToU electricity tariffs, $P_{L,t}^{\omega_{L,t}}$ and $P_{PV,t}^{\omega_{PV,t}}$ are the generated load and solar profiles from the sets of all generated load and solar profiles $\Omega_{L,t}$ and $\Omega_{PV,t}$, respectively. $P_{g,t}$ is the power demanded from grid at time t; a penalty factor k is applied to the objective function to ensure that the PEV storage can reach the target state-of-charge (SOC) level SOC_{tar} before leaving the residential system. $SOC_{t,leave}$ is considered as the charge level when PEV will leave the household. It is important to notice that it is not possible for the PEV battery to charge above its target level at the end of the charging process due to the effect of the penalty factor k as it will significantly increase the total cost. C_d is another penalty factor which is assigned to avoid discharging of the PEV, $P_{d,t}^{PEV}$ during off-peak hours. If this penalty term is not introduced in the objective function, then the PEV will discharge up to the threshold level to minimize the cost function. If the PEV discharges during off-peak hours to its threshold level, it will have to charge again to reach its target level for the next day. As charging during off-peak hours is economical, it will prefer to regain charge during the off-peak hours. So, charging and discharging during off-peak hours will not be economical, and will cause energy losses. To avoid discharging during off-peak hours, this penalty cost is introduced, which is chosen between the value of partial peak and off peak ToU rates. The objective function J and model constraints are written as:
Subject to:

$$J = min\Bigg[\sum_{t=1}^{T}(C_t P_{g,t} + |SOC_{t,tar}^{PEV} - SOC_{t,leave}^{PEV}|k + C_d P_{d,t}^{PEV})\Bigg] \tag{4}$$

A. Power balance constraint [27]:

$$P_{g,t} - P_{c,t}^{PV} + P_{d,t}^{PV} - P_{c,t}^{PEV} + P_{d,t}^{PEV} - P_{def,t} = P_{L,t}^{\omega_{L,t}} - P_{PV,t}^{\omega_t} \tag{5}$$

B. Charge balance constraint [24]:

$$SOC_t^{PEV} = SOC_{t-1}^{PEV} + \frac{P_{c,t}^{PEV}\Delta t\eta}{Q_{PEV}} - \frac{P_{d,t}^{PEV}\Delta t}{Q_{PEV}\eta} \tag{6}$$

$$SOC_t^{PV} = SOC_{t-1}^{PV} + \frac{P_{c,t}^{PV}\Delta t\eta}{Q_{PV}} - \frac{P_{d,t}^{PV}\Delta t}{Q_{PV}\eta} \tag{7}$$

C. Charge and discharge operational limits based on PV and load respectively [25]:

$$P_{c,t}^{PV} \leq P_{PV,t}^{\omega_{PV,t}} \tag{8}$$

$$P_{d,t}^{PV} - P_{c,t}^{PEV} \leq P_{L,t}^{\omega_{L,t}} \tag{9}$$

$$P_{d,t}^{PV} + P_{d,t}^{PEV} \leq P_{L,t}^{\omega_{L,t}} \tag{10}$$

$$C_t^{off-peak} \leq C_d \leq C_t^{partial-peak} \tag{11}$$

$$k \geq 0 \tag{12}$$

D. Non-negativity requirement for purchases from the grid [25]:

$$P_{g,t} \geq 0 \tag{13}$$

E. Upper and lower bounds for the model decision variables [24]:

$$SOC_{min}^{PEV} \leq SOC_t^{PEV} \leq SOC_{max}^{PEV} \tag{14}$$

$$SOC_{min}^{PV} \leq SOC_t^{PV} \leq SOC_{max}^{PV} \tag{15}$$

$$P_c^{PEV\_min} \leq P_{c,t}^{PEV} \leq P_c^{PEV\_max} \tag{16}$$

$$P_d^{PEV\_min} \leq P_{d,t}^{PEV} \leq P_d^{PEV\_max} \tag{17}$$

$$P_c^{PV\_min} \leq P_{c,t}^{PV} \leq P_c^{PV\_max} \tag{18}$$

$$P_d^{PV\_min} \leq P_{d,t}^{PV} \leq P_d^{PV\_max} \tag{19}$$

where $\omega_{L,t} \in \Omega_{L,t}, \forall t \in T$, and $\omega_t \in \Omega_{PV,t}$.

In the system under consideration, $P_{def,t}$ is defined to be the deferred energy amount (i.e. solar generation curtailment), $P_{c,t}^{PV}$ and $P_{d,t}^{PV}$ are the PV based energy storage instantaneous charging and discharging power, $P_{c,t}^{PEV}$ and $P_{d,t}^{PEV}$ are the PEV battery instantaneous charging and discharging power. SOC_t^{PV} and SOC_t^{PEV} are the energy storage and PEV state-of-charge at time t. The lower and upper bounds of decision variables are provided in Table I. The parameters Q_{PV} and Q_{PEV} are the total capacity, η_{PV} and η_{PEV} are the storage charger efficiency and the PEV charger efficiency, respectively. If the load demand exceeds PV generation, then the additional power needed to satisfy the household demand that can come from either the energy storage discharged power or purchased power from the grid. In this scenario, it is less efficient to charge the storage according to (5) - (7). On the other hand, if PV generation is higher than the demand, the surplus will be stored in the battery (if there is storage capacity available) and there will be no discharge. Thus, charging and discharging of the storage device simultaneously is not possible. Due to similar reasons, simultaneous charge and discharge of PEV-storage device is also not possible.

This problem is based on two basic assumptions: First, the grid can only deliver power to the household; there is no net metering compensation provided. Second, the PV-storage device can only be charged by using solar PV generation and both storages discharge only to deliver power to the household. We choose to represent such problem as a multi-stage stochastic programming model and then the SDDP algorithm is employed to solve it. The SDDP solution procedure is briefly discussed in the following subsection using a general model.

C. Multi-stage Stochastic Optimization

The SDDP algorithm avoids the well-known curse of dimensionality of Dynamic Programming (DP) by constructing an approximation of the future cost function with piecewise linear functions represented through Benders' cuts that are added iteratively as the algorithm proceeds [28]. The process stops when a stopping criterion is reached. For simplification, a general T-stage stochastic linear program for the problem at hand can be formulated as follows:

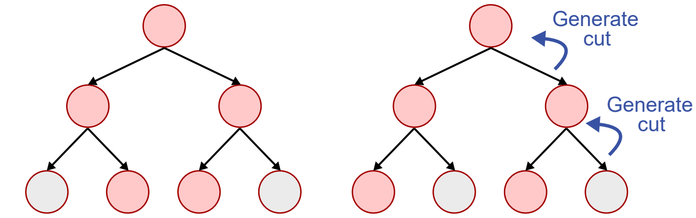
$$h_t(x_{t-1}, b_t) = \min_{x_t} \left[c_t x_t + \mathbb{E}_{b_{t+1}|b_t} h_{t+1}(x_t, b_{t+1}) \right] \tag{20}$$

Subject to:

$$A_t x_t = B_t x_{t-1} + b_t : \pi_t \tag{21}$$

$$x_t \geq 0 \tag{22}$$

The decision variables of a particular stage t are considered as a vector x_t, which includes electricity purchases from the grid, power charge and discharge, and SOC levels for the storage devices. Parameter b_t represents the stochastic PV generation and load at stage t. Equation (20) represents the model objective function designed to minimize the total cost that includes present and expected future costs. Equation (21) is the representation structural constraints (5) - (7) and (9) – (10). Dual variables (denoted by π_t) derived from the transition constraints are used later to construct a piece-wise linear approximation of the future cost function following Benders' decomposition scheme [28], [29]. Equation (22) represents simple bounds on the decision variables such as (8), (11) - (19). The realization of the random parameter b_{t+1} affects the condition of the system at stage t. Thus, $\mathbb{E}_{b_{t+1}|b_t} h_{t+1}(x_t, b_{t+1})$ carries out the expected cost function of stage $t+1$ given the decisions x_t in stage t.



(a) Forward pass on selected samples (b) Backward pass on selected samples

Figure 3: SDDP solution process applied to a three stage and two scenarios per stage problem.

A visualization of how the SDDP works to solve this problem is depicted in Figure 3, which shows the process for a simple three-stage problem. Once a sampled scenario tree like Figure 3 (a) is available for the SDDP, the process is started by sampling highlighted forward paths to proceed for the forward pass. During the forward pass, a sequence of models like (20) - (22) is solved at each time stage using the simplex method. During the solution process, Benders' cuts which are accumulated from previous iterations for the certain stage, are used as additional constraints to create a better approximation of the future costs and improve the decision-making process [28], [29]. At the final stage of the forward pass, the total expected cost is estimated and it is considered as the upper bound of the problem. The lower bound for the sampled problem is calculated from solving the first stage problem during forward pass considering the present and future expected cost. If the lower bound cost reaches a stopping criteria (defined here to be within a 95% confidence interval of the upper bound cost as in [29]), the SDDP process is stopped. Otherwise, iteration process will continue till the desired convergence level is reached. At each iteration, new forward paths are sampled independently in the scenario tree. For reaching the desired convergence level, the algorithm proceeds to the backward pass shown in Figure 3 (b). In the backward pass, the algorithm computes new Benders' cuts for previous stages to improve the approximations of the future cost functions at each stage, for more details see [28], [29]. This process does not require the algorithm to discretize the state and decision spaces, which results in less computation time and memory requirement.

IV. Simulation Results and Analysis

In this section, the computational results are illustrated to show the impact of coordinated control. The system parameters used for simulation analysis are listed in Table I. Forecasted solar generation profile for a summer day and a typical household summer load profile are obtained from [30] and [31]. They are shown in Figure 4. The correlation coefficient between them for this case study is -0.15. The ToU rates for residential customer varies during the day based on off-peak, partial peak and peak hours; a representative ToU rates available from the utility are used for the analysis and is given in Table II [32]. PEV is considered to be plugged into the system at 18:00 hr with 40% of SOC and it is assumed that it will leave at 07:00 hr on next day with

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Table I: System Parameters

Parameters	Values
Solar PV panel installed power capacity	3 kW
PV based battery capacity (Q_{PV})	4 kWh
PEV battery capacity (Q_{PEV})	85 kWh
η_{PEV}, η_{PV}	92%
Initial SOC_t^{PV}	20%
Initial SOC_t^{PEV}	40%
SOC_{min}^{PEV},SOC_{min}^{PV}	20%
SOC_{target}^{PEV}	80%
SOC_{min}^{PEV},SOC_{min}^{PV}	20%
$P_c^{PV\_max}$,$P_d^{PV\_max}$	3 kW
$P_c^{PV\_min}$,$P_d^{PV\_min}$	0 kW
$P_c^{PEV\_max}$,$P_d^{PEV\_max}$	20 kW
$P_c^{PEV\_min}$,$P_d^{PEV\_min}$	0 kW

Table II: ToU Rate

Season	Load Type	Period	ToU Rate ($\$/kWh$)
Summer & Fall (June-September)	Off-peak	21:00-9:00	0.15
	Partial-Peak	10:00h-13:00h & 19:00h-21:00h	0.226
	Peak	13:00h-19:00h	0.342
Spring & Winter (October-May)	Off-peak	20:00-15:00	0.15
	Peak	17:00h-20:00h	0.17

the desired SOC of 80%. We have assumed that the PEV charging pattern is deterministic based on user input data in this algorithm. In a future research, additional source of uncertainty from PEV usage in addition to electricity demand and solar PV generation uncertainties can be explored. The model's objective is to control the charging/discharging actions of the storage devices to minimize the overall cost to the customer in a particular day. The effects on the battery lifetime are assumed to be negligible for the purpose of this analysis, since vehicle traction batteries are designed to undergo frequent charge/discharge cycles and are expected to be able handle the additional cycles. Nevertheless, the lifetime effect could potentially be assessed by incorporating a battery degradation model such as those reported in [33], but this extended research is beyond the scope of this paper.

SDDP solves the multi-stage stochastic program designed for the problem and provides control policies to the PV-based storage and PEV storage to increase cost savings per day. The optimization problem is solved in MATLAB on an Intel Core i5-4600U with a 1-GH CPU, 4 GB of RAM, and 64-bit operating system PC. For comparison, a strategy based on heuristic control is considered [34]. In the heuristic control strategy, PV based storage is charged when there is an excess of solar generation (above the demand) and discharged when the load is higher than the solar generation. The PEV starts charging up to its target level whenever it is present at the grid in heuristic control. Impact of standalone control of PV-based energy storage control and PEV storage control are also shown in result analysis.

A. *Effects on electricity purchase savings*

The SOC profiles of PV based storage and PEV storage for these two control strategies are shown in Figure 5 and Figure 6. From Figure 5, it can be seen that PV based storage

Table III: Comparison of peak hours energy savings for different methods on different seasons

Control strategies	Summer	Fall	Winter	Spring
Heuristic control	30%	21%	0.01%	0.30%
SDDP based control on PV storage and heuristic control on PEV storage	31%	22%	5.7%	5.7%
Heuristic control on PV storage and SDDP based control on PEV	96%	99%	97.5%	97.4%
SDDP based coordinated control	93%	99.7%	99.9%	98%

prefers to charge during off-peak and partial-peak hours and discharge during peak hours for coordinated control. It also started charging when PEV leaves from house in the morning. Before that, PV generation is utilized to charge the PEV which is shown in Figure 6. Since PV generation is utilized to charge the PEV, there remains more capacity for PV based storage to store solar energy for coordinated control. As a result, PV based energy storage has reached its threshold level later than the heuristic control during higher solar generation period on Figure 5. Since there is more storage capacity available during high solar generation period for coordinated control, less solar generation loss is ensured than the heuristic control.

From Figure 6, it is shown that PEV based storage starts to discharge during peak hours to meet the household demand if coordinated control is applied. Due to this reason, load profile in Figure 7 is lower for coordinated control during peak hours. But PEV storage SOC increases for the heuristic control, as it starts charging whenever it is present in the house. So, the load profile in Figure 7 increases for heuristic control during peak hours. As for our case study, we have assumed that PEV will leave in the next day at 07:00 hr and the PEV battery started the charging process during the off-peak period for the coordinated case to avoid the defined penalty in the objective function. Thus, the load profile in Figure 7 increases during the off-peak hours to charge the PEV to reach at the target SOC level for the coordinated control. If a customer wants to get rid of PEV excess charging costs, it is possible to define a different target SOC level.

Simulations are performed for different seasons due to the variation of load demand, solar generation and ToU rates. The impact of standalone SDDP based control for PV storage with heuristic control of PEV, and standalone SDDP based control for PEV storage with heuristic control of PV based storage to minimize costs are also considered. The comparison of the electricity purchase costs from the grid for different control strategies is shown in Figure 8. It is found that the proposed coordinated control strategy outperforms all other control strategies. The results show that coordinated control saves approximately 37% of the costs during summer days and 12.7% during winter days compared to the heuristic control case. If the average of these savings is considered, it can be said that the proposed coordinated control strategy can save approximately 26% of the electricity purchase cost compared to the heuristic control method annually.

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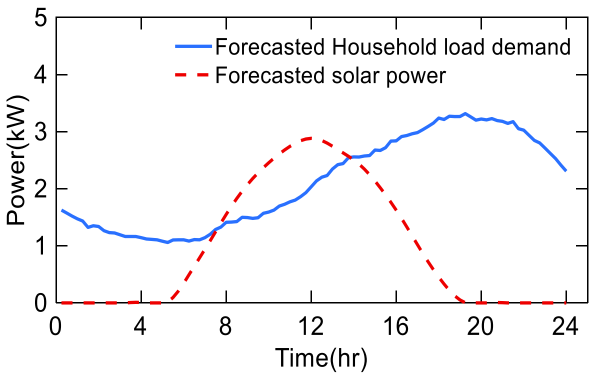

Figure 4: Household and solar generation profile.

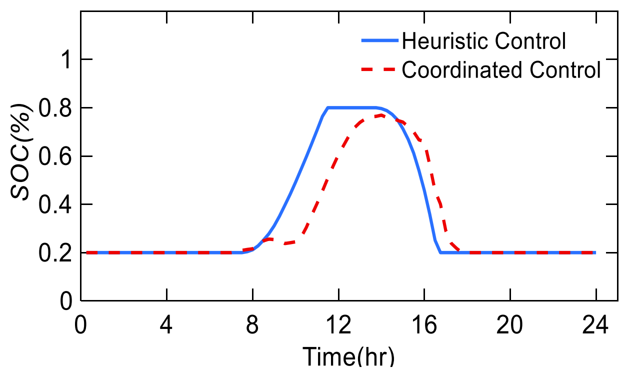

Figure 5: SOC profiles of PV-based storage.

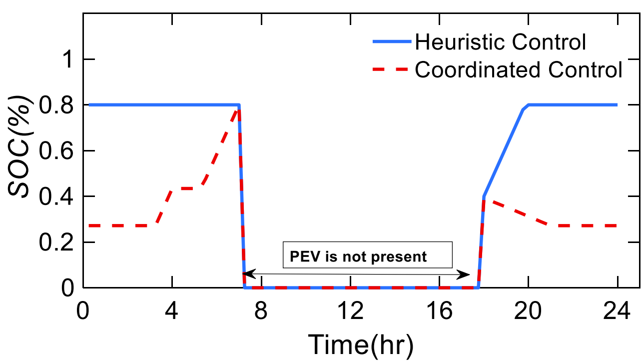

Figure 6: SOC profiles of PEV storage.

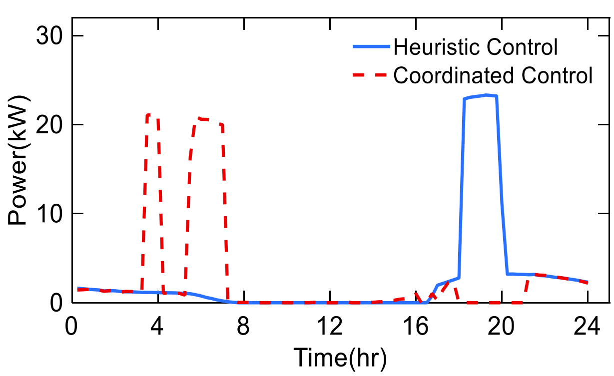

Figure 7: Household load profile after control.

Table IV: Solar generation usage when PEV is present from 18:00 hr for different seasons

Control strategies	Summer	Fall	Winter	Spring
Heuristic control	67.7%	59%	100%	100%
SDDP based control on PV storage and heuristic control on PEV storage	100%	100%	100%	100%
Heuristic control on PV storage and SDDP based control on PEV	68%	59%	100%	100%
SDDP based coordinated control	100%	100%	100%	100%

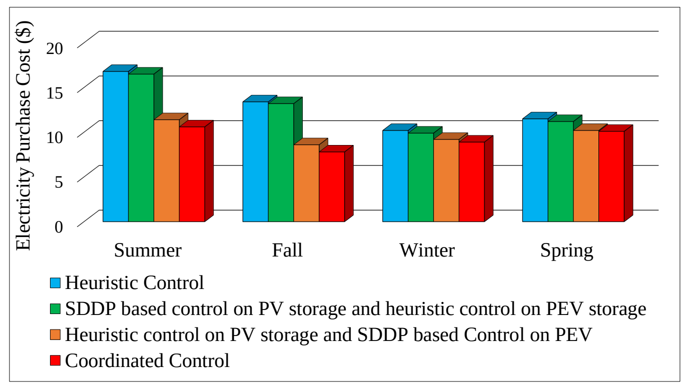

Figure 8: Comparison of electricity purchase cost per day for different methods on different seasons.

B. Effect on peak hour energy savings

Peak hour energy savings help utility companies to avoid various grid problems such as load variation and congestion or higher local marginal prices. For different methods, peak hour energy savings for different seasons are also calculated and the values are depicted in Table III. As the heuristic method prefers to discharge PV based storage while load is higher than PV generation and does not consider cost savings, peak hour savings are comparatively lower during summer and fall for this method. There is no peak hour saving for winter and spring as energy storage discharges before peak hour period in this method. For coordinated control, the objective function is to reduce overall electricity purchase cost per day. It tries to reduce peak-hour electricity purchase from the grid by utilizing solar generation and stored energy from energy storage and PEV as much as possible. Thus, peak hour savings are always higher for the coordinated control method.

C. Effect on PV generation usage

The more solar PV generation will be utilized to mitigate demand, the less energy will be required to be purchased from grid, which is the objective function of our proposed method. As a result, it can be seen that PV generation usage is 100% on our proposed method in Table IV. The level of 100% utilization of solar generation gives the maximum return on the investment and the largest cost savings to the user. When PV based storage is controlled through the SDDP based method, it also ensures 100% utilization of solar generation for all seasons. However, with heuristic control of energy storage, solar generation is deferred during summer and fall

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Table V: Computation time for different methods for a summer day when PEV is present from 18:00 hr.

Control strategies	Computation time
Heuristic control	4s
Heuristic control on PV storage and SDDP based control on PEV	63s
SDDP based control on PV storage and heuristic control on PEV storage	142s
SDDP based coordinated control	207s

due to less available capacity of energy storage during higher solar generation period shown in Figure 5. PV generation usage becomes comparatively lower for this control strategy on energy storage presented on Table IV. During winter and spring seasons, solar generation is lower than the demand. Thus, all methods can utilize the solar generation.

D. Computation time

Due to scenario generation, correlation consideration, and iteration process to reach the stopping criteria, the SDDP algorithm requires comparatively higher time than the heuristic control strategy. With the increase of the number of scenarios considered during forward and backward pass, simulation time increases. Compared to the heuristic control strategy, the SDDP method requires more computation time. For 50 forward and 20 backward pass consideration, computation time requirement for different methods are shown in Table V. The data in Table V illustrates that due to the increase of the model size and the uncertainty representation in the SDDP control approach, the computation time increases. Although longer computational time is required for the SDDP application, the increase in time is not unreasonable. The energy management control periods are designed in the scale of minutes and the SDDP-based approaches can meet the requirements with some additional computational resources. There is also room for improvement in the SDDP convergence algorithm to minimize the computational time [35].

V. Conclusion

The importance of coordinated control between PV-based storage and PEV storage is reported in this paper for a residential system to minimize the overall electricity purchase cost from the grid. Uncertainties in PV generation and load demand are considered in the system to test different control methods. The correlation between these two uncertain parameters is computed and used together with a Cholesky decomposition approach to generate future scenarios. To ensure PEV charging level for the next day according to the owner's preference and to avoid discharging of PEV during off-peak hours, penalty costs are introduced in the objective function of the model. The SDDP algorithm is then applied to solve the optimization problem under uncertainty. SDDP helps the decision maker to control the charge and discharge profiles of both the storage components and minimize the overall cost for the customer. The results from the SDDP based strategy with the coordinated control scheme show that by controlling the PV-based storage and the PEV storage power flow in the system, it is possible to optimally purchase electricity from the grid and simultaneously satisfy the household demand. The simulation results validate that the coordinated control scheme achieves lower electricity purchase cost compared to heuristic control or standalone application of SDDP to PV-based storage or standalone application of SDDP to PEV storage. It also increases peak hour energy savings, and PV usage for all seasons comparative to other methods. The methodology discussed here can be further expanded to coordinated control among many different storage units and renewable sources under uncertainty.

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