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Energy management and optimal storage sizing for a shared community: A multi-stage stochastic programming approach

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HIGHLIGHTS

- We propose a cost-effective energy management algorithm for PV-storage in the context of a shared community.
- Uncertainties related with electricity demand and solar power generation are used in the decision-making process.
- The impact of energy management is included for net present value (NPV) calculation of each system design.
- An approach to identify the optimal storage sizing using NPV is presented and applied to each house of the community.

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ABSTRACT

The aim of this paper is to propose a new energy management framework and storage sizing for a community composed of multiple houses and distributed solar generation. Uncertainties associated with solar generation and electricity demand are included to make the mathematical models more realistic, and as a result, provide more accurate control strategies to manage storage devices utilization. To evaluate that, a multi-stage stochastic program model designed to minimize community electricity purchase cost per day is used to support decision-making by creating control policies for energy management. Two different strategies are created to represent the interest of a single household (the individual energy management - IEM) and households that share their assets with the community (shared energy management - SEM). Our strategies consider time-of-use rates (*ToU*), load and resource variation during different seasons, with their distinct days of the year, to calculate net present value (NPV) associated with the energy savings. IEM and SEM are then used in a framework designed to establish the requirement of optimal energy storage size for each house of the community based on NPV values. The results of this study for an analysis considering a community with five houses show that the proposed SEM strategy reduces the overall electricity purchase costs for a summer day up to 11% and 3% compared with heuristic and IEM control respectively. Moreover, our results suggest that the application of the methodology increases peak energy savings up to 17%, scales up solar generation usage up to 23%, and the optimal storage size obtained in the shared community case reduces up to 50%.

1. Introduction

Solar photovoltaic (PV) energy is emerging as one of the most effective and important alternatives of distributed generation resources at the household level. Integration of rooftop solar PV is considered as an interesting investment opportunity to reduce electricity purchases from the grid and to provide cost savings to homeowners. Sadly, the use of solar PV generation alone may not be extremely attractive because the generated electricity cannot always be used to supply the demand when needed. Most of the electricity production from solar PV panels is available during daytime when the owner is less likely be at home (smaller demand) and cannot be used to supply demand at night time. Thus, energy storage devices are often considered as an alternative to be used alongside with solar PV panels to store surplus energy and deliver it to the homeowner when needed. Energy storage devices may not only increase solar PV energy usage but also reduce the homeowner's electricity purchases from utility distribution grid. However, these devices may not always be considered as the most economical

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Nomenclature

Acronyms

PV	Solar photovoltaic technology
IEM	Individual energy management based-strategy
SEM	Shared energy management based-strategy
ToU	Electricity time-of-use rates

Indices & sets

T	Set of time periods indexed by t in [minute]
Ω_t^{PV}	Set of stochastic scenarios for solar generation at stage t for all houses
Ω_t^{L}	Set of stochastic scenarios for electricity demand at stage t for all houses
s	Number of seasons of the year
k	Solar panel life time in [years]
I	Set of houses indexed by i *or* j
N	Total number of houses

Parameters

R	Correlation matrix between electricity demand and solar PV generation estimated from past data
L	Cholesky decomposition matrix
Y	Base scenario matrix
X	Independent draws for solar generation and electricity demand matrix
C_t	Electricity time-of-use (*ToU*) rate at stage t in [\$/kWh]
$\hat{y}_{t,i}$	Scenario realization value of the i^{th} house at stage t in [kW]
C_t	Electricity time-of-use (*ToU*) rate at stage t in [\$/kWh]
Δt	Time interval in [minute]
$P_{dem,t}^{i,\omega_t}$	Household electricity demand forecast of the i^{th} house at stage t in [kW]
$P_{PV,t}^{i,\omega_t}$	Solar generation at scenario ω of the i^{th} house at stage t in [kW]
η	Energy storage device charging/discharging efficiency
$\underline{SOC}^i$	Minimum state of charge (*SoC*) for the i^{th} storage device in [%]
$\overline{SOC}^i$	Maximum state of charge for the i^{th} storage device in [%]
$\underline{P}_C^i$	Minimum allowable power charge for the i^{th} storage device in [kW]
$\overline{P}_C^i$	Maximum allowable power charge for the i^{th} storage device in [kW]
$\underline{P}_D^i$	Minimum allowable power discharge for the i^{th} storage device in [kW]
$\overline{P}_D^i$	Maximum allowable power discharge for the i^{th} storage device in [kW]
ω_L^i	Sampled electricity demand profile of the i^{th} house at stage t in [kW]
ω_{PV}^i	Sampled solar photovoltaic (PV) generation of the i^{th} house at stage t in [kW]
G_t	Cut gradient matrix
g_t	Cut intercept vector
C_b	Battery investment cost during solar PV panel life time in [\$]
q	storage size in [kWh]
Ψ	Number of replacements for storage devices
γ	Storage device cost in [\$/kWh]
F_s	Energy savings during season s in [kWh]
r	Discount rate
F_k	Energy savings during year k in [kWh]
ΔToU	Deviation of *ToU* rate
q_i	Optimal storage size for the i^{th} house based on IEM control in [kWh]
Q_c	Overall optimal storage size for the community based on SEM control in [kWh]
Q_i	Storage size for the i^{th} house based on SEM control in [kWh]

Decision variables

$P_{g,t}^i$	Electricity purchases from the i^{th} house at stage t in [kW]
$P_{C,t}^i$	Charging power from the storage of the i^{th} house at stage t in [kW]
$P_{D,t}^i$	Discharging power from the storage of the i^{th} house at stage t in [kW]
$P_{i-j,t}^j$	Power generated from the i^{th} house and received by the j^{th} house at stage t in [kW]
$P_{j-i,t}^j$	Power generated from the j^{th} house and sent to the i^{th} house at stage t in [kW]
$P_{def,t}^i$	Deferred solar PV energy from the i^{th} house at stage t in [kW]
SOC_t^i	Storage state-of-charge of the i^{th} house at stage t in [kW]
x_t	Decision vector at stage$t$
P_k	Net savings obtained in year k in [\$]

Functions

$h_{t+1}(.)$	Recursive function
$\mathbb{E}_{b_{t+1}\mid b_t} h_{t+1}(x_t, b_{t+1})$	Expected cost function of stage $t+1$
$\lvert\cdot\rvert$	Represents the cardinality of a set, i.e., the number of elements in that set.
NPV	Net present value

solution for investment at the individual household level due to their investment costs [1,2]. Nonetheless, shared utilization of energy storage may be viewed as a robust and attractive alternative to a community as a whole [3]. Recent work [4] argues that the reduction in costs of energy storage and the increasing demand for local flexibility are creating possibilities for storage devices to be deployed at local communities. Shared energy storage not only brings economic benefits to the users but also helps to improve peak shaving and solar PV usage when compared with a system considering individual PV-based storage devices.

This paper presents a new energy management framework that accommodates the uncertainties of electricity demand and solar PV generation. We use results from different energy management strategies to propose optimal storage capacity sizing for a community of households, which is an essential step for maximizing the benefits for individuals. The idea of energy sharing at the community level has gained attention recently [5]. The work of [6] proposed a simulation method to obtain energy the sizing of storage systems for a community where the levelized cost of electricity and other metrics are evaluated. The significance of community storage in microgrids for load smoothing and peak shaving based on model predictive control for time-of-use (*ToU*) rate has been discussed in [7]. The authors in [8] proposed a two-level hierarchical optimization method for microgrid community and community level devices' energy management system to minimize operational costs considering deterministic demand and renewable generation in a smart grid environment. A modified auction based on joint energy storage ownership scheme has been suggested in [9] for a number of households to determine the fraction of their energy storage capacity that they were willing to share with the community. The work presented in [10] adopted a dynamic noncooperative game with a decentralized approach to determine the optimal energy trading for the day-ahead considering energy surplus from solar PV generation in community with energy storage devices. Another technical approach using community energy storage was proposed in [11] to overcome the shortcomings of an unbalanced allocation of one-phase solar PV units. The work of [12] investigates the use of community energy storage to perform solar PV energy time-shift and demand load shifting for two distinct scenarios in the United Kingdom. But none of these works considered the uncertainties associated with electricity demand and solar PV generation in the context of the energy management problem.

Uncertainty associated with wind power generation has been considered in multi-stage stochastic programs by [13], where the authors propose the use of the Stochastic Dual Dynamic Programming (SDDP) algorithm to prescribe the amount of energy to procure, store and discharge from the storage in a microgrid configuration. The SDDP, that was initially developed by [14], has been applied with a lot of success in the energy literature over the years in centralized planning / dispatch schemes [15] with conventional generation [16] and renewable generation [13], but the application of such algorithm in modern power systems with distributed generation resources and battery storage is limited with one analysis of energy storage at the household level [17] and one devoted to analyze the use of batteries from electric vehicles to reduce household electricity costs [18]. In [19], a study about charging and discharging behaviors of energy storage devices among residents in a cooperative community is carried out, where electricity prices are considered as a source of uncertainty and a genetic algorithm is employed to operate the system. Previously referenced literature have not considered the variation of weather affecting variables and parameters of interest, which has been considered in [20], based on 1-day ahead forecasts. The work reported in [21] represents a stochastic model of a community including wind power generation and a storage system. But none of these works considered the creation of control policies for storage devices based on multi-stage stochastic programming models.

Similar to energy management strategy for storage, different tools for energy storage sizing [22] to shift generation and reduce prosumers' usage in a community have been proposed in [23]. Uncertainties in solar PV and wind energy for capacity sizing of a community storage have been included in the analysis presented in [24], although the scheduling of charging and discharging operations for energy storage devices have not been considered. The work of [25] employs the remaining power curve method considering the uncertainties related to solar PV generation and electricity demand to determine the minimum energy storage requirement to install devices at different locations seeking to prevent overvoltage issues. A two-stage stochastic programming model has been suggested in [26], where the goal was to determine the optimal size for storage devices along with their control strategy considering uncertainty introduced by wind power forecast errors. The authors in [27,28] used a probabilistic-based approach to reduce back feeding of energy into the grid. All these papers have not discussed the impact of overall economic benefits considering the savings from shared energy management strategy for storage sizing of individual members of a community, which is the primary concern of this paper.

The overall goal of this research is to achieve reductions in total costs for a community, including electricity purchases per day from the utility company and energy storage devices investment costs associated with each house in the community. In this regard, we carry out energy management for a community composed of several houses (each with their own solar PV generation and storage devices) to attain individual household's needs while minimizing the overall electricity purchase costs of the community. The energy management is performed through the individual energy management (IEM) and shared energy management (SEM) control strategies obtained by solving multi-stage stochastic programs. In this novel approach, we explore a more realistic representation of the stochasticity associated with solar PV generation and electricity demand, and also create a mechanism to represent the potential correlation between these two uncertain sources and establish an accurate and reliable energy management framework. As the importance of correlation between electricity demand and solar PV is noted in [29], Cholesky decomposition [30] is used to represent the correlation in within the model framework, similarly to what was done in previously in [31] for wind and water inflow scenario generation and [32] for solar PV and load at the household level. Moreover, we employ the SDDP algorithm to solve multi-stage stochastic programs and

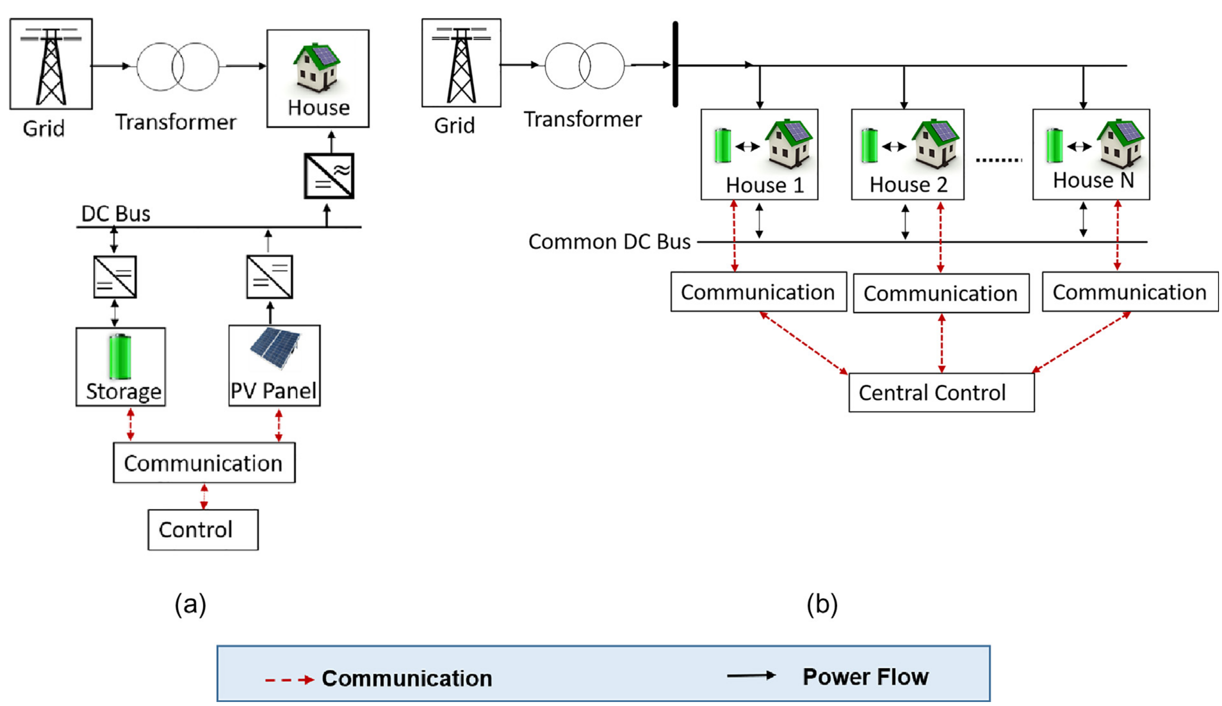

Fig. 1. Systems considered for designing energy management strategies. (a) Individual PV-storage system for IEM strategy, (b) Shared community system for SEM strategy.

establish reliable control strategies (IEM and SEM) for the problem. Finally, we seek to maximize the economic benefits for each individual house when defining the optimal storage sizing for the community. This approach considers different storage sizes in combination with the IEM and SEM strategies to estimate the energy net savings and define the optimal configuration based on net present values (NPV) [33]. The methodology developed here is general and can be used for designing any system with distributed generation and shared storage devices considering uncertainties.

The remainder of the paper is organized as follows: Section 2 presents the stochastic energy management problem for the community system, the scenario generation procedure, the multi-stage stochastic program formulation, and the storage capacity sizing method. Simulation results from our proposed methodologies are presented in Section 3. Section 4 provides a discussion on storage sizing and performance improvement based on the simulation results and Section 5 concludes this paper.

2. Stochastic energy management and storage sizing strategies

2.1. Energy management strategies

An individual owned solar PV-based storage system and a community system composed of N houses are shown in Fig. 1(a) and (b) respectively. The hybrid PV-panel and battery system is considered to be connected on a DC bus. The IEM strategy is designed considering the system depicted in Fig. 1(a) and it is used for energy management in each separate house that is part of the community system. To ensure a higher ratio of solar utilization, we assume that the storage devices are not allowed to store energy by charging from the grid.

The SEM strategy is designed considering together all the households that are part of the community along with their respective solar PV panels and storage devices as the system depicted in Fig. 1(b). In this scheme, energy produced by solar PV panels from all houses can flow between the storage devices and the households through a common dc bus [34]. The inverters of the storage devices are considered to have bidirectional capabilities; however, this is used only to satisfy the needs within the community. We assume that the storage devices will only store energy generated from the solar PV panels and discharge to meet the different household demands, but as in the IEM strategy it is not allowed to store electricity from grid purchases and there is no back-feed power to the utility grid. More details of how the IEM and SEM strategies are created can be found in Section 2.4.

The shared community system can be managed by a communication system composed of smart meters and a charge control unit as described in [35]. The central controller communicates with each house to control the usage of the overall solar PV production between households and charge/discharge patterns of the storage devices through an energy management scheme, which is shown in Fig. 2. Data from electricity demand forecasts as well as solar PV generation are required to use in an optimization model designed to create the control policies and use them to obtain the optimal energy management including handling storage devices' charging/discharging and power flow among the houses in a given day. For solar PV generation and electricity demand information, a stochastic representation based on data from point forecasts is employed in the scenario generation procedure (Section 2.2 and Supplementary information). It is assumed that each house will receive an equal amount of credits that will be compensated by the other houses that will use their generated solar PV considering the utility *ToU* rate as a monetary metric. In this assumption, we consider that the smart meter can measure the electricity usage from the grid and also can track the generated solar PV provided to the community from each household.

2.2. Scenario generation procedure

One important step to model and solve the energy management problem under uncertainty (or stochastic energy management) in a multi-stage context is to develop a scenario tree to represent possible events associated with the existent random parameters. Solar PV generation and electricity demand are sampled from probability distributions, defined using information based on existent data, in order to construct a sampled scenario tree with different scenarios. A straightforward way to model random variables that represent solar PV generation and electricity demand in a scenario tree is to assume that vectors are interstage independent, similar to the procedure described in [36]. Inter stage independence from one period to the next means that the realization of the random variable at a future stage has no relationship with the realization of random variables from previous stages. As solar generation and electricity demand varies due to weather, temperature, cloud cover and other patterns it is reasonable to assume that this information can be treated as independent over time, something similar was done by [37] to forecast solar radiation. For example, one could imagine a forecasting model (e.g. a Multi-layer perceptron neural network model) for electricity demand based on temperature forecasts, i.e., once trained, this model would receive future temperature forecasts and come up with demand forecasts without relying on the previous information.

In order to generate more realistic scenarios for demand and solar PV generation, it is important to represent the correlation between these two random variables. To accomplish that, we use past data to estimate the existing correlation between solar PV generation and electricity consumption. Once the correlation is computed, one way to represent this information and generate combined scenarios for solar PV generation and electricity demand is to perform independent draws from normal distributions $\mathcal{N}[\mu, \sigma^2]$ (where μ is the average and σ^2 is

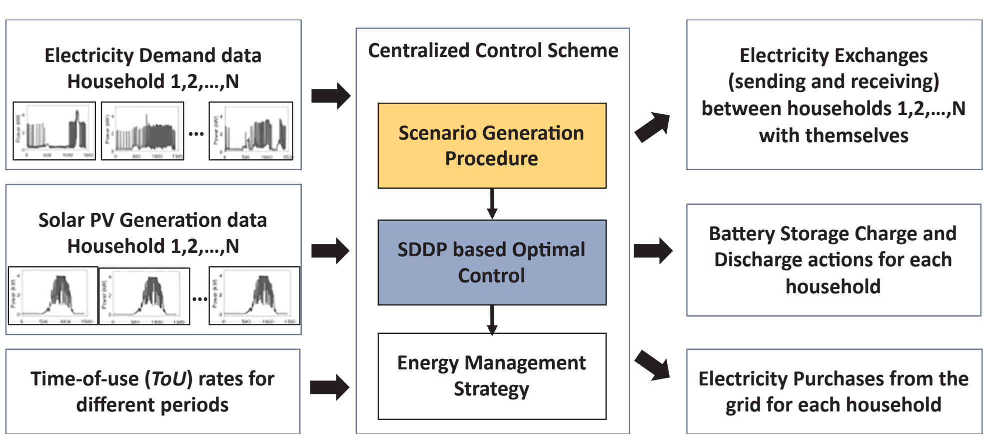

Fig. 2. Proposed framework for central control based on a shared community system with solar PV and storage.

the variance of the probability distribution) and then pass the correlation between the parameters using the Cholesky decomposition approach [32]. Suppose the number of stages is T and number of uncertain parameters is n. Let X be a matrix $(T \times n)$ with independent identically distributed draws from a normal distribution $\mathscr{N}[0, 1]$, and let R be the correlation matrix between electricity demand and solar PV generation. The Cholesky decomposition of R is a lower triangular matrix L such that:

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

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

where Y will then be a matrix with correlated draws. Thus, Y will correspond to draws from $\mathscr{N}[0, \Sigma]$. The original draws are from a $\mathscr{N}[0,1]$, and the covariance matrix $\Sigma = R$. If we want correlated draws for electricity demand and solar PV generation, for households $i = 1, 2, ...,N$ at some stage t given by $\mathscr{N}_{j,i}[\mu_i, \sigma_i^2]$, we can multiply the draws from column i of the Y matrix by σ_i and add the mean μ_i associated with electricity demand (when generating values for demand) and solar PV generation (when generating values for solar PV) that were estimated using past data. For example, an element of the matrix Y, say $y_{j,i}$ corresponding to the j-th draw, can be defined as (3):

$$\hat{y}_{j,i} = \mu_i + y_{j,i}\cdot\sigma_i \tag{3}$$

Thus (3) will be a draw from $\mathscr{N}[\mu_i, \sigma_i^2]$. By following this procedure it is possible to generate scenarios for our random parameters taking into account the correlation structure among them. We note that during the time periods that correspond to the night time, the scenario realizations of solar PV generation are considered to be zero and the correlation between electricity demand and solar PV generation is not considered. In other words, during the night period, the generated solar PV generation values are zero and random for the electricity demand, which are generated considering only its own probability distribution. We note that a description of a procedure to generate a interstage independent scenario tree with correlated draws is presented in the Supplementary information.

2.3. Mathematical model formulation

The model formulation under specific scenario realizations defined by ω for the energy management of the shared community is presented in (4)–(11). The model's objective function defined by z is represented in (4), where the goal is to minimize electricity purchases from the grid. In this setting, a one-day cycle from 0 hr to 24 hr with a 1-minute resolution is considered. The models' constraints are stated in (5)–(11). The forecasted household electricity demand and corresponding solar PV generation profiles for N houses are used as input for the community system model and represented in the scenario ω realization, in other words, $P^{i,\omega_t}_{dem,t}$ and $P^{i,\omega_t}_{PV,t}$ are changed based on each individual household and scenario realization.

A. Electricity purchases cost minimization:

$$z = \min \sum_{t=1}^{|T|} \left(C_t \cdot \sum_{i=1}^{|I|} P^i_{g,t} \right) \tag{4}$$

where z represents the deterministic model objective function value; T represents the set of time stages indexed by t; I is the set of houses indexed by i *or* j; $|\cdot|$ represents the operator that defines the cardinality of the set, i.e., the number of elements in that set. For example, $|I|$ is equal to N, which is the number of houses in the community; C_t is the electricity *ToU* rate at stage t; $P^i_{g,t}$ is the electricity purchases from the grid by household i at period t.

B. Power balance constraint for each individual house:

$$P^i_{g,t} = P^{i,\omega_t}_{dem,t} - P^{i,\omega_t}_{PV,t} + P^i_{C,t} - P^i_{D,t} + \sum_{j=1, j\neq i}^{N} P^j_{i-j,t} - \sum_{j=1, j\neq i}^{N} P^j_{j-i,t} + P^i_{def,t},\ \forall\ t \in T, \forall\ i \in I \tag{5}$$

Based on Eq. (5), the amount of power exchanges among houses can be determined by analyzing the variables $P^j_{i-j,t}$ and $P^j_{j-i,t}$. Here, $P^i_{def,t}$ is the deferred solar PV power, $P^i_{C,t}$ is the charge and $P^i_{D,t}$ is the discharge power of the storage device from house i. This information also can be used to compute the net credit and the electricity bill per day for each house. It ensures that the deferral of generated solar PV energy, also referred in the literature as solar curtailment [38], is reduced by allowing the model to exchange the produced energy exchanges with other houses. This idea presents a new and important model enhancement that to our knowledge was not previously considered in the related literature such as the work of [39].

C. Charge balance constraint for the individual house:

$$SOC^i_t = SOC^i_{t-1} + \frac{P^i_{C,t}\eta\Delta t}{Q_i} - \frac{P^i_{D,t}\Delta t}{Q_i\eta},\ \forall\ t \in T, \forall\ i \in I \tag{6}$$

where SOC^i_t defines the state of charge of the storage device i for particular time t. Constraint (6) has the purpose to track the state of charge associated with the energy storage devices over time. This constraint is responsible to couple decision stages in time as well.

Based on the modeling choice, constraint (7) limits the charging capabilities of the storage device at each time stage to the sum of solar generation produced at that time.

$$\sum_{i=1}^{n} P^i_{C,t} \le \sum_{i=1}^{n} P^{i,\omega_t}_{PV,t},\ \forall\ t \in T \tag{7}$$

As the back-feeding power to the grid causes over-voltage in the distribution network, as reported in [40] and as well as in many other places, constraint (8) is introduced to avoid this issue.

$$\sum_{i=1}^{n} P^i_{g,t} \ge 0,\ \forall\ t \in T \tag{8}$$

D. Upper and lower bounds for decision variables for individual houses:

$$\underline{SOC}^i \le SOC^i_t \le \overline{SOC}^i,\ \forall\ t \in T, \forall\ i \in I \tag{9}$$

$$\underline{P}^i_C \le P^i_{C,t} \le \overline{P}^i_C,\ \forall\ t \in T, \forall\ i \in I \tag{10}$$

$$\underline{P}^i_D \le P^i_{D,t} \le \overline{P}^i_D,\ \forall\ t \in T, \forall\ i \in I \tag{11}$$

2.4. Energy management problem as a multi-stage stochastic program

The model described by (4)–(11) presents a deterministic model that optimizes overall time stages under specific realizations of the uncertainty parameters. However, it is not realistic to assume that such model is a proper representation of the problem at hand due to the variation of the electricity demand and solar PV generation throughout the day. Instead, we aim to represent such model considering different possible realizations of the random parameters at each time stage with the goal to hedge against uncertainty. In this setting, we represent our model according to the class of multi-stage stochastic programs [41], where we consider a scenario tree representation to properly represent the uncertainty parameters and the dynamics between decisions that are coupled in time. We follow the notation from [42] to design a general T-stage stochastic linear program with recourse for the problem as stated by (12)–(17).

$$\min_{x_1} c_1x_1 + \mathbb{E}_{b_2|b_1}h_2(x_1, b_2) \tag{12}$$

$$\text{s. t.}\quad A_1x_1 = B_1x_0 + b_1 \tag{13}$$

$$x_1 \geq 0 \tag{14}$$

where for $t = 2, ..., T$,

$$h_t(x_{t-1}, b_t) = \min_{x_t} c_t x_t + \mathbb{E}_{b_{t+1}|b_t} h_{t+1}(x_t, b_{t+1}) \tag{15}$$

$$\text{s. t.} \quad A_t x_t = B_t x_{t-1} + b_t \tag{16}$$

$$x_t \geq 0 \tag{17}$$

The decision vector x_t for a particular stage t, is represented by the model decision variables related to electricity purchases from the grid, storage device charge/discharge actions, and SOC. The A_t term represents the model's structural constraint matrix at stage t that captures (5)-(8). The term $B_t x_{t-1}$ represents the storage in the system that is carried forward from stage $t-1$ and is available at stage t. Solar PV generation and electricity demand at stage t are considered to be the model stochastic parameter represented by b_t. The model objective functions designed to minimize the total cost of the system are related to the first and to the t^{th} stage costs respectively and are provided in (12) and (15) with the addition of their associated expected recourse function. The model's structural constraints for power and charge balance requirements from (5) and (6) as well as maximum charging capabilities (7) and no back feeding power to the grid (8) are represented as components of (13) and (16). Simple bounds for decision variables are represented in (14) and (17). It is important to note that the realization of random parameter b_2 affects the conditions of the system at stage 2 as well as the elements of the decision vector x_1 that carries information about storage levels to the future; the same idea follows for random parameter b_{t+1}, the decision vector x_t and the model at stage $(t+1)$. A detailed multi-stage stochastic formulation for the energy management problem can be found in the Supplementary information document.

To solve the model (12)–(17), we make use of the SDDP algorithm. The SDDP algorithm has been successfully used in the literature for solving multi-stage stochastic linear programs in different types of applications. The SDDP helps to avoid the curse of dimensionality of Dynamic Programming (DP) by constructing an approximation of the future cost function with piecewise linear functions represented through Benders' cuts. These cuts are added iteratively until the process stops when the stopping criterion is reached [14]. Dual variables are derived from the structural constraints (14) and (17) and used to construct a piece-wise linear approximation of the future cost function at each stage following the Benders' decomposition method [43]. The SDDP algorithm was computationally implemented using MATLAB [44], and CPLEX [45] is used as the optimization solver engine.

The SDDP represents a master program at each stage, which accumulates Benders cuts and creates in that way an approximation to the expected future cost function. Let $\vec{G_t}$ and $\vec{g_t}$ denote a cut-gradient matrix and a cut- intercept vector. Each backward pass of SDDP along a sample path (there are two in Fig. 3) augments $\vec{G_t}$and $\vec{g_t}$ with one additional row. We define a stage t model that serves as a master program with respect to its stage $t+1$ descendants and as a subproblem with respect to its stage $t-1$ ancestor:

$$z_t = \min_{x_t, \theta_t} c_t x_t + \theta_t \tag{18}$$

$$\text{s. t.} \quad A_t x_t = B_t x_{t-1} + b_t \text{: } \pi_t \tag{19}$$

$$-\vec{G_t} x_t + e\theta_t \geq \vec{g_t} \tag{20}$$

$$x_t \geq 0 \tag{21}$$

Note that when applying the SDDP the recursive function is replaced by a decision variable θ_t. The variable θ_t used in the objective function in (18) together with (20) will form an outer linearization of $\mathbb{E}_{b_{t+1}|b_t} h_{t+1}(x_t, b_{t+1})$ at stage t. In (18) z_t represents the objective function value at stage t, obtained after the model is optimized, and in (20) e is a vector with values equal to 1. Constraints (19) and (21) are the same constraints previously presented in (16) and (17) respectively. Model (18)–(21) holds for all stages except the last stage T, where the constraint set (20) is absent. The π_t represent dual (row) vectors associated with constraints (19) and (20), respectively. Model (18)–(21) is the one solved at each node in the forward and backward paths in Fig. 3.

A simple three-stage problem along with a visualization of how the SDDP algorithm is used to solve the problem is depicted in Fig. 3. However, it is important to mention that for the problem defined above, the tree sizes of interest are quite large. For example, for the system considered as our case study, a tree with 100 scenarios per stage with 1441 stages. Based on the available forecasted scenario (Fig. 3(a)), a sampled scenario tree shown in Fig. 3(b), is formed for the SDDP using (1)-(3) and the SSTIISC algorithm described in the Supplementary information. Then, sampled forward paths are considered for the algorithm to proceed in the forward pass (highlighted in the tree of Fig. 3(c)). A forward path is a sequence of nodes starting at the root node of the tree and following a unique forward sequence of nodes until

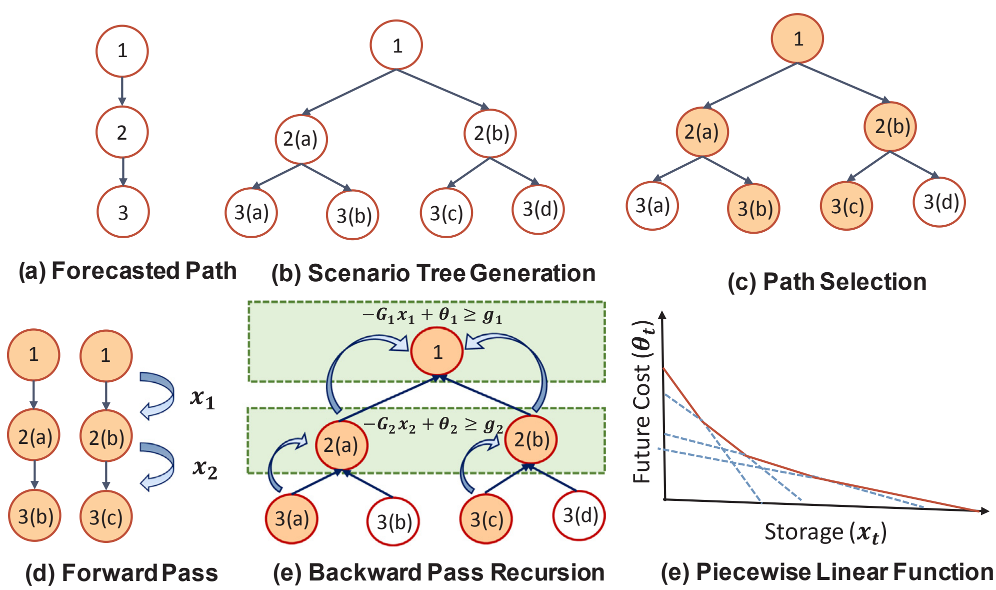

Fig. 3. Multi-stage stochastic optimization solution process via SDDP.

it reaches its endpoint at one leaf node of the tree. A sequence of models based on (18)–(21) is solved at each time stage using the simplex method to solve the linear programs. Benders' cuts, which are accumulated from previous iterations for each time stage, are used as additional constraints to create a better approximation of the future costs and improve the decision-making process. In this process, a sample mean estimator of the costs associated with all the sampled forward paths in the scenario tree, is constructed and considered as the upper bound of the sampled multi-stage stochastic program. A lower bound for the sampled multi-stage program is obtained from solving the first stage problem, model (18)–(21) when $t = 1$. The stopping criteria considered for this work, assumes that if the difference between the lower bound and the upper bound estimators reaches a $(1 - \alpha)\%$ confidence interval, with α usually defined to be 0.05, the SDDP process is stopped. Otherwise, the iteration process will continue until the desired convergence level is reached. Other more efficient stopping criteria [46] were investigated in the literature such as in the work of [47] and [16], however, in this work we consider the stopping criteria proposed by [14]. During each iteration of the algorithm, new forward paths such as those shown in Fig. 3(d) are sampled independently from previous iterations in order to better explore the solution space and achieve a proper convergence of the algorithm. In Fig. 3(d), x_1 and x_2 are represented as decision vectors with values optimized at time stage 1 and 2, consequently.

Similar to the forward pass, independent scenarios are sampled (highlighted nodes) for the backward pass. Fig. 3(e) portrays the cuts corresponding to new constraints to be added at each stage. To compute Benders' cuts, the SDDP can select a subset of the sampled paths. The backward pass requires more computational time than the forward pass. Therefore, the number of selected paths in the backward pass is often chosen to be smaller than the forward pass to reduce SDDP iteration time. After cuts are computed in the backward pass for all the stages, a new set of sampled forward paths from the scenario tree is solved using the accumulated Benders' cuts obtained thus far. For more details about a general SDDP algorithm to be applied to model (18)–(21) as well as the general cuts computation see [42]. For more details about the version of the SDDP algorithm and the cuts computation for the energy management problem refer to the Supplementary information.

We note that both the IEM and SEM control strategies are obtained by applying the SDDP algorithm to the multi-stage stochastic programs designed for the individual house or shared community case respectively. The application of the SDDP to the multi-stage stochastic programs yield a collection of Benders' cuts (see Section 2.4 and the Supplementary information) at each time period t. These cuts, during the normal SDDP procedure within a sampled scenario tree (Fig. 3), are used to achieve the convergence of the algorithm. However, after the convergence of the algorithm is achieved, these cuts are considered as the policy that will indicate the decisions. These decisions should be made based on the realization of the uncertainty parameters, for more details see [48]. Therefore, the collection of cuts, i.e. control strategies, obtained by the application of the SDDP are applied to tighten the feasible region of the energy management models that operate with out-of-sample information (i.e. with scenarios generated that are not in the sampled scenario tree) and provide decisions regarding charge and discharge actions, power exchanges and electricity purchases.

2.5. Determination of energy storage capacity for each household

We aim to create a strategy to define the best energy storage capacity for each household in the community. We consider NPV results associated with energy savings in the analysis considering both, the individual household case and the shared community case. NPV is a metric used in capital budgeting to analyze the profitability of an investment and has been used over the years in many energy-related applications to evaluate investments in electricity generation, transmission and distribution assets [49–52]. The NPV is established by considering the difference between the present value of cash flows and the present value of cash outflows. A positive NPV indicates that the projected earnings generated by a project exceed the anticipated costs. Generally, an investment with a positive NPV will be a profitable one and an investment with a negative NPV will result in a net loss. The main advantage of using NPV is to quantify how much the project will impact the position of the capital initially invested. We also choose to use the more robust and detailed NPV metric over the classic payback method because the latter does not provide any guidance regarding the investor cash flows.

For a single house storage sizing, the net savings obtained from applying the IEM control strategy is investigated. For the annual energy savings calculation, a variation of ToU rates during summer and winter

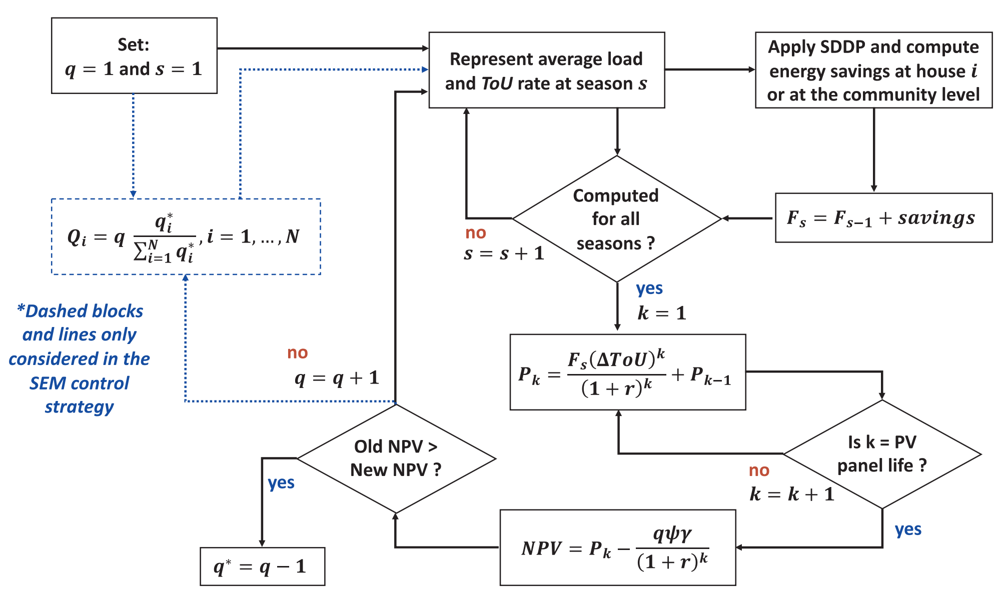

Fig. 4. Flowchart for optimal storage size calculation for the IEM and the SEM control strategies. The flowchart is applied to each house individually in the IEM control strategy case to obtain q^* and then we set $q_i^* = q^*$. In the SEM control strategy case q_i^* was previously defined from the results of the IEM analysis and q^* is obtained for the community, and so we set $Q_c^* = q^*$. Note the dashed lines and blocks are only considered in the SEM control strategy case.

seasons is considered according to the *ToU* rate structure from PGE [53]. Electricity demand for each house and solar PV generation profile also change according to the season of the year and has an impact on the NPV results, this has been omitted in previous related work such as [54] and [27,28]. For simplification to calculate storage sizing, annual electricity demand profiles of a particular house can be divided into four seasonal demand profiles: spring, summer, fall, and winter. Four average electricity demand profiles are obtained from past data to represent the different houses in the community system. The SDDP algorithm is then applied to each individual house (using the IEM control strategy) considering the household-specific electricity demand profile for each season and the corresponding *ToU* rates to minimize the electricity purchases from the distribution grid. The cumulative sum of energy savings for all the seasons provides the net annual savings for each individual house. In order to compute the NPVs associated with the problem, a discount rate is used to bring the future cash flows to the current date [27,28]. Based on the discount rate, NPVs are calculated by considering the energy savings and the costs associated with batteries replacement based on their life cycle. Expenditure of battery for the projected time period is calculated using (22).

$$C_b = \frac{q.\ \Psi.\ \gamma}{(1+r)^k} \tag{22}$$

Here q represents the storage capacity, Ψ respresents number of replacements for storage devices during the life time of PV panel, γ represents storage device cost in per kWh, r represents discount rate and k represents years. As the project span is based on the solar PV panel life, we consider that the *ToU* rate will vary during this period. In order to represent future increase in *ToU* rates, we use past data available for a 10 years period provided in PGE [53]. We average the variations in *ToU* rates and incorporate this average to represent future rate grows that are then considered in the calculation of the future net energy savings. In our setup, the NPV is the difference between the savings and expenditures for the entire project lifetime of 20 years, considering (23).

$$NPV = \sum_{k=1}^{K} \frac{F_s(\Delta ToU)^k}{(1+r)^k} - C_b \tag{23}$$

Here, F_s is the net annual savings calculated from energy management strategy, ΔToU is the change of ToU rate for PV panel over years and K is the life-time of PV panel. The flowchart for the NPV based calculation and the determination of optimal energy storage capacity based on the IEM and SEM control strategies for each house and the community is provided in Fig. 4.

We utilize the results of the energy storage sizing discussed above for each individual house of the shared scenario. This procedure will help us to avoid an exhaustive search process by varying the energy storage size of each individual house in the community one by one and find the optimal NPV for the whole community. Thus, the optimal storage size q_i^* for each house is calculated following the flow chart from Fig. 4. These results help us to get the idea that if a house has lower electricity demand and higher solar PV generation, then its individual storage capacity requirement is higher than the other houses of the community, which will be reflected between the ratio of the q_i^* and the total individually controlled optimal storage capacity of all houses. Thus, for each of the variation of total community storage, Q_c the storage size of each house, Q_i follows Eq. (24).

$$Q_i = Q_c \frac{q_i^*}{\sum_{i=1}^{N} q_i^*} \tag{24}$$

After getting the storage size for each house, Q_i the SDDP is runs based on the SEM method to find out the net energy savings. The NPV is computed in a similar manner to the IEM control strategy case. The highest NPV value ensures the optimal storage size Q_c^* for the whole community, where Q_c^* is divided among the houses of the community by following Eq. (24). From the power balance defined in (5), it is possible to calculate how much power is exchanged between houses. If a house is sending power to another house, we assume that it will get an equal amount of credit computed using the energy amount and the *ToU* rate from the utility company. This energy credit for the first house is a debt. The house that receives energy has to payoff to maintain fairness in the community in terms of exchanges.

3. Case study and simulation results

3.1. System configurations and data

In order to investigate the importance of the SEM strategy for a community system, we consider the analysis of the two systems depicted in Fig. 1. The goal is to evaluate the benefits for the community as a whole and each individual house that is part of that community when the energy management is performed at the system level. Although the analysis is performed considering four seasons of the year and their associated typical days representing different electricity demand and solar PV profiles, we concentrate here in showing the results only for a typical summer day. The *ToU* rates considered to represent the price that the customer has to pay for electricity purchases from the grid in a summer day is shown in Fig. 5 and obtained from PGE [53]. The household electricity demand profiles of five houses along with their corresponding solar PV generation profiles from the same spatial area are obtained from [55] and shown in Fig. 6. It is to mention that, *ToU* rates (provided in the Supplementary information) also change for different seasons, and this is considered when applying the SDDP algorithm to solve the model. We note that the *ToU* rate considered here does not include demand charges at the residential level, therefore, this *ToU* structure is simply composed of energy charges. However, if a different *ToU* structure was to be considered with the addition of demand charges, similar to [56], the control strategies presented here would again attempt to reduce the overall costs by reducing the peak energy utilization from the grid. Moreover, following the proposed control strategies would potentially help to reduce the community demand contracts with utilities, due to a smaller peak demand, which would potentially incur smaller demand charges and larger benefits to the community.

The parameters considered for NPV analysis for the different system configurations are listed in Table 1.

For the purpose of this specific case study, a community system composed of five houses is considered. It is important to note that the analysis carried out in this study can be performed for a community with any number of houses. We represent that each individual house has solar PV panels and electricity storage device installed. Therefore, each house will produce solar PV generation and has its own electricity demand, these parameters are considered as the sources of uncertainty in the analysis.

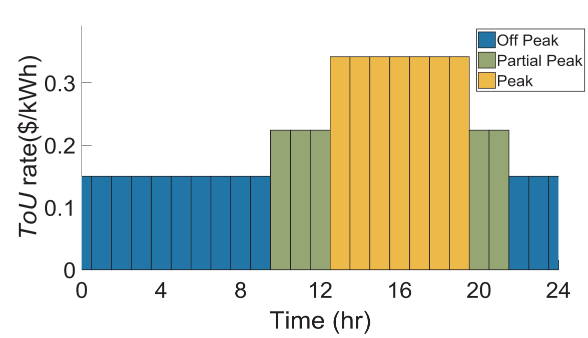

Fig. 5. *ToU* rates for a typical summer day [53].

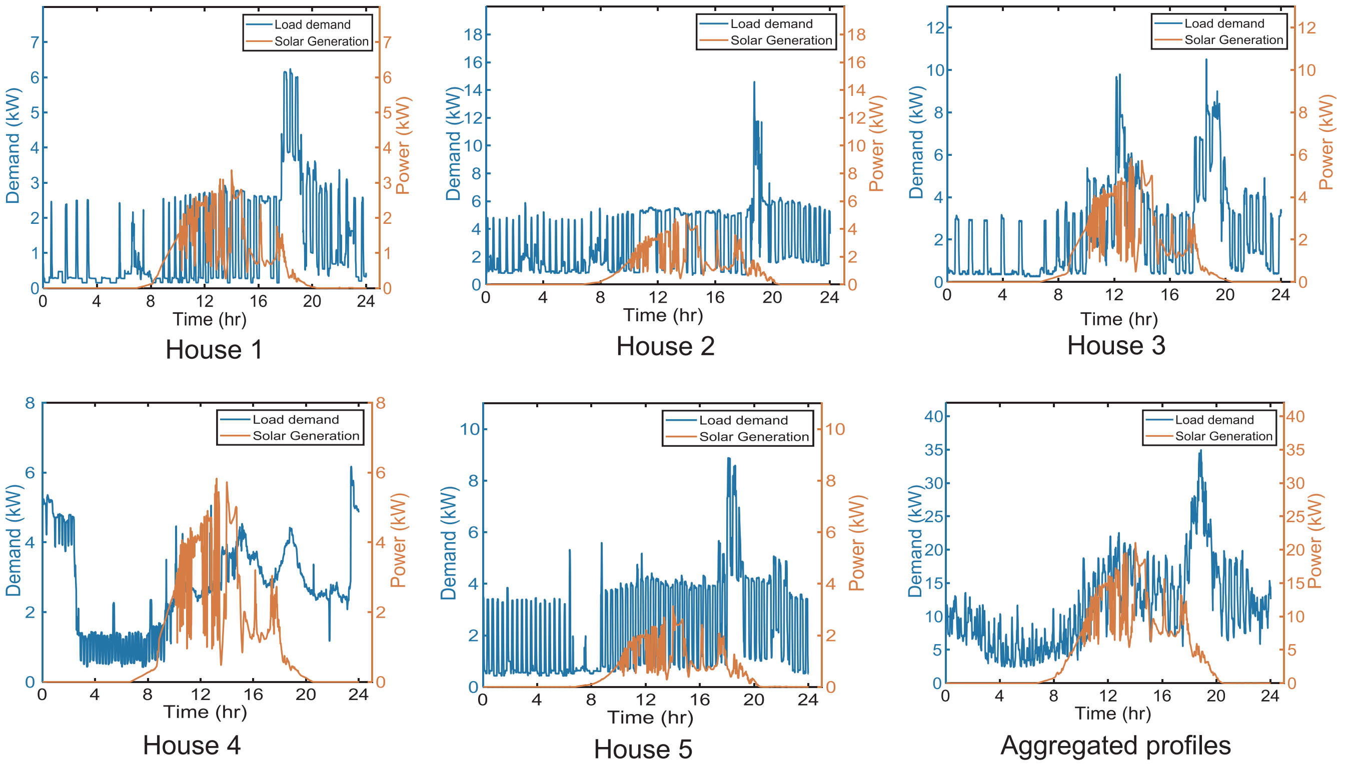

Fig. 6. Electricity demand and solar generation of five houses on a summer day and their aggregated demand and solar generation profiles.

Table 1
Data regarding the net present value analysis for the system.

Parameter	Value
PV panel lifetime	20 years [64]
Battery lifetime	7 years
Battery capacity (houses)	0–7 kWh
Battery capacity (community)	5–10 kWh
Battery cost	\$350/kWh [65]
Efficiency, η	0.92
InitialSOC	20%
$\underline{SOC}$	20%
$\overline{SOC}$	80%
$\underline{P}_C$, $\underline{P}_D$	0 kW
$\overline{P}_C$, $\overline{P}_D$	5 kW

3.2. SDDP algorithm application

The simulation results show the benefits of applying the SDDP algorithm to establish the IEM and SEM control strategies, with the goal to minimize electricity purchases from the grid on a typical summer day. A scenario tree with 100 scenarios per stage with 1441 stages is constructed using $\mathcal{N}$ [0,1] to create inter-stage independent scenarios at each stage. The SDDP is applied to the scenario tree in order to obtain the policy (collection of Benders cuts at each stage) for both, the IEM and the SEM strategies. For comparison, a heuristic control policy is also considered. For the heuristic control strategy, solar PV based storage is charged when there is an excess of solar generation (more than the demand) and the device is discharged when the household demand is higher than the solar generation [57].

From Figs. 7 and 8, it can be observed that when the *ToU* rate is lower and solar energy is available, the household storages undergo charging. Thus, the load profile of the IEM and SEM does not change although there is solar generation during that time. The storage devices discharge during partial-peak and peak-hour periods and maintain enough capacity to store solar energy production when demand is lower than the electricity produced in order to reduce the purchase costs from the grid. As a result, the aggregated electricity demand during peak-hours is comparatively lower for IEM and SEM control strategies. But as it can be observed by following the SEM control strategy the system can store more solar generation (surplus) than in the IEM strategy case, therefore, the SEM strategy helps to alleviate demand during peak time more than the IEM strategy. With closer observation during peak hours in Figs. 7 and 8, one can notice peak demand reduction from adopting the SEM control strategy.

The SDDP is applied to the households with their corresponding solar and demand profiles for standalone IEM control. To compare the impact of different control strategies, a policy evaluation analysis is performed by generating 1000 independent and random forward paths to represent future possible scenario realizations for the uncertainty parameters considering the summer season (when the demand and solar generation are at their peak). The policies obtained by running the SDDP in the original scenario tree are then separately applied to each individual forward path and the model (4)-(11) is simulated to minimize the cost at each stage of each forward path scenario. Then the average value of 1000 profiles (each representing the sum of the costs

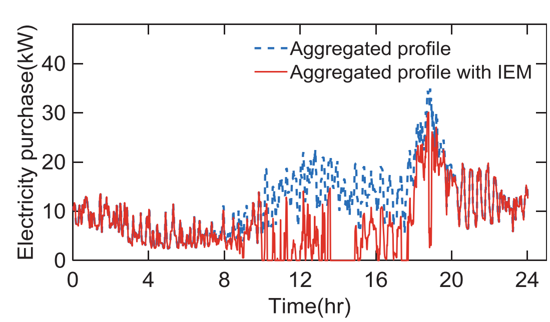

Fig. 7. Electricity purchases from the grid with and without the IEM control strategy.

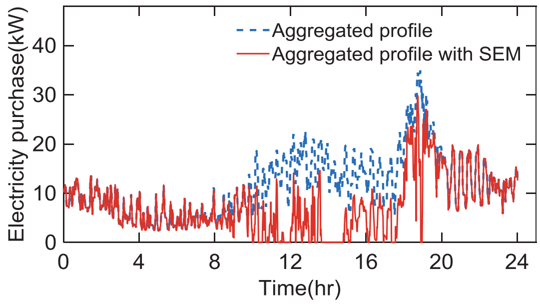

Fig. 8. Electricity purchases from the grid with and without the SEM control strategy.

of all the stages associated with one forward path scenario) for each house is considered as the point estimator for the total cost in our analysis. During our simulations, the optimal storage capacity is used for each house (more details are discussed in the next subsection). The comparison results of energy purchases from the grid for each house, overall peak shaving, and solar PV generation usage are presented in Tables 2 and 3. Our results show that the suggested shared storage usage along with the SEM control strategy outperforms the individual ownership storage with heuristic or IEM control strategies in terms of minimization of net electricity purchase costs for the homeowners. We also have conducted a similar analysis for demand and solar PV profiles of three other seasons considering the *ToU* rate for the corresponding seasons. The electricity purchase savings from grid for different methods are shown in Fig. 9. It ensures the total electricity consumption reduces in the SEM control strategy for all seasons compared to other methods.

3.3. Individual versus shared storage capacity sizing for each household

The optimal capacity of storage sizes for the IEM and SEM control strategies for five houses are calculated based on the method discussed in Section 2.5. The results of NPV calculation for five houses based on the IEM strategy are shown in Fig. 10. Fig. 11 presents the NPV calculation results based on the SEM strategy applied to the aggregated profile. The optimal storage sizes are selected based on the maximum NPV values for both control strategies. For the SEM control strategy, following Eq. (24), the storage size for each house is calculated. The comparison of storage sizes for five houses based on the IEM and the SEM control strategies with the proposed sizing method is shown in Fig. 12. To increase the surplus solar PV generation usage, a comparatively higher storage capacity is required for individually owned and controlled storage devices. On the other hand, the household with surplus solar PV generation receives equal credits valued by *ToU* rate to supply the excess energy to the other houses that participate in the community SEM control strategy. Therefore, the houses with higher solar PV generation will prefer to save the energy produced for meeting their peak demand first and then send the excess to the other houses in order to meet other community needs instead of storing in their batteries. This allows for the individual storage devices capacities to be reduced for each house when we compare to the IEM control strategy case. Though the capacity of storage reduces for SEM control strategy, the overall solar PV energy usage increases. Thus, the storage sharing will provide benefits for individual houses with a reduction in their electricity purchase and investment costs.

The comparative results between the IEM and the SEM control strategies are presented in Fig. 13. The cost and the storage capacity size reductions improve the NPV in the SEM control strategy compared to the IEM control strategy. Due to the comparatively higher electricity purchase costs shown on Table 2, it is expected that the heuristic control strategy will show lower NPV than the IEM and the SEM control strategies for the same size of storage. Thus we have not shown the comparison of storage size for heuristic control strategy.

4. Discussions

Our research presents the fact that shared based storage systems are cost-effective as found in previous literature such as [58] and [59]. However, the community-based energy storage system proposed in previous research, require separate space in the community to settle down the role of central energy storage systems. Also, the ownership of the previous community-based energy storage systems is still a topic in debate. References [6,39] proposed a third-party distribution network operator or aggregator which will be required to own storage and control aggregated load demand and generation. In that case, each household will have a probability to lose some economic benefits compared to the individually owned energy storage system. Community storage options might become invaluable for houses in this regard. The SEM control strategy proposed in our work does not require any separate installation like a central community storage in a particular place. Therefore, there will be no arguments about the ownership of the third party. All participated households will have their own storage devices installed in this system architecture. The storage devices will be centralized controlled to minimize the overall electricity purchase costs per day.

Other goals and characteristics could be explored in future studies within the framework developed here such as minimization of electricity losses, representation of ancillary services [60], representation of the transmission and distribution networks, among other things. These considerations are beyond the scope of this paper as our focus is directed to create efficient control policies to hedge against uncertainties in demand and supply and use them to investigate the economic benefits for households in a community; however, they would be interesting directions for future research. In our proposed methodology, it is ensured that individual owners will benefit more using the SEM control strategy than the IEM control strategy in two aspects - overall electricity purchases from the grid and smaller storage devices size. It is to be noted that the energy storage sizing method and the proposed investment plan can also be analyzed by computing other financial metrics such as the payback period associated with the investment as done in [61]. Moreover, consideration of exergy analysis for energy storage devices as performed for batteries in [62] and for a drying plant in [63] could be potential directions for future studies.

Moreover, we aim to keep a fair compensation scheme in the system to ensure that the household with comparatively higher energy production - demand usage ratio will receive larger benefits through the proposed SEM control strategy, which has not been explored in previous literature such as (Barbour et al., 2015). In terms of optimal storage sizing requirements for each house, it is also emphasized in the proposed storage sizing method that the household with lower generation and higher demand during peak hours should have lower size than the other houses. As the excess amount of generation from one house is used by another house, usage of solar PV generation is also increased when compared to the IEM and heuristic control strategy. Another important aspect of this research is that our model will avoid over voltage issues by not allowing back-feed power to the main grid,

Table 2
Electricity purchase costs of each house ($/day) for a summer day when no storage is used and different control strategies are used.

	Heuristic	IEM	SEM
House 1	4.7	3.8	3.6
House 2	12.2	11.5	11.3
House 3	8.3	7	6.7
House 4	6.5	6.2	5.8
House 5	9.7	9.5	9.4
Total	41.4	38	36.8

Table 3
Comparison of different control strategies for a summer day using the aggregated profile of the community.

	Heuristic	IEM	SEM
Electricity purchase ($/day)	41.4	38	36.8
Peak energy savings (%)	43.74	45.5	60.4
PV usage (%)	74.9	93.3	97.8

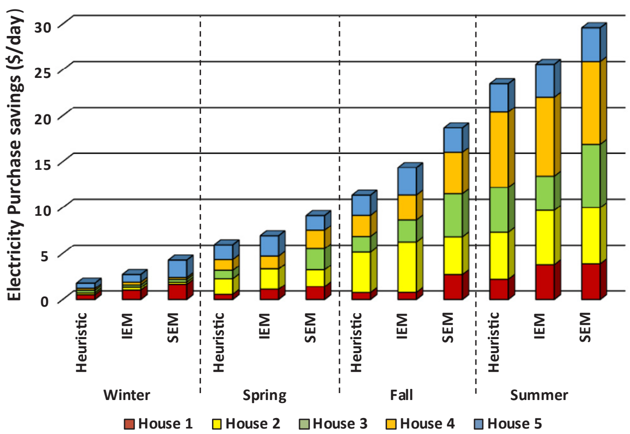

Fig. 9. Comparison of electricity purchase savings per day (from electricity purchase without solar) for different seasons and different control strategies.

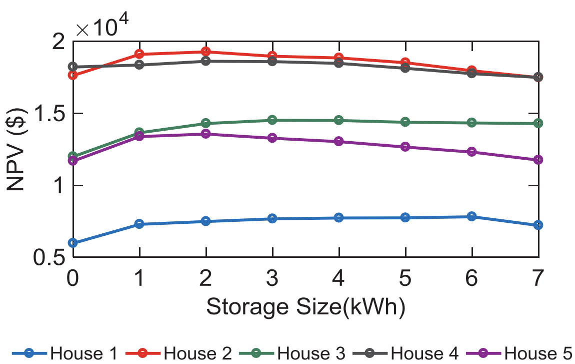

Fig. 10. NPVs of houses for different storage sizes for IEM control.

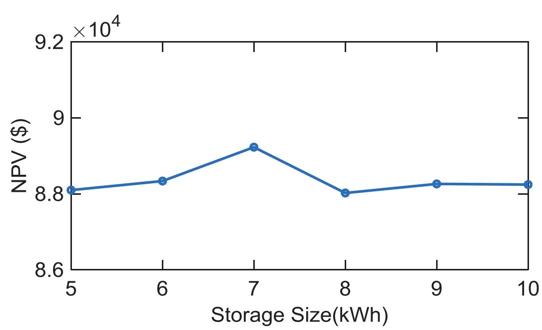

Fig. 11. NPVs of different storage sizes for SEM control.

this was represented as a hard constraint in our formulation. Future studies could analyze the problem with back-feeding power capabilities and also explore possibilities to charge the storage devices using electricity from the grid during off-peak periods. We finally note that degradation costs of the storage devices have not been considered in our model, and to be conservative we considered a modest life time for batteries (7 years), however, more detailed degradation models could be incorporated within the analysis framework in future studies. Also,

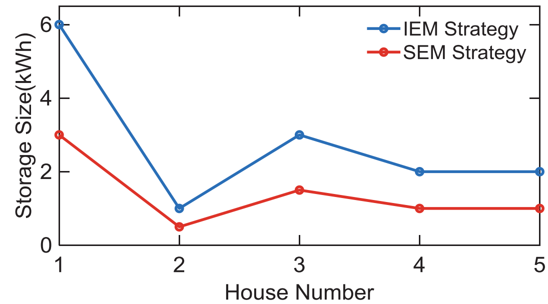

Fig. 12. Comparison of optimal storage sizes for different houses for IEM and SEM control strategies.

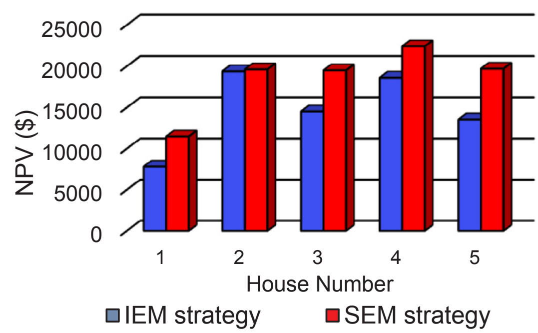

Fig. 13. Comparison of NPVs for different houses for IEM and SEM control strategies.

the development of IEM and SEM strategies rely on the assumption of interstage independence for generating scenarios associated with the random variables, future studies could further develop the ideas presented here to address inter stage dependency cases following the ideas presented in [36] and [42].

5. Conclusions

A novel framework for energy management in a system composed of renewable energy and storage devices for a community system is presented. We represent the energy management problem as a multi-stage stochastic program, where solar PV generation and electricity demand are represented as uncertainties. We obtain the optimal charge/discharge patterns of the energy storage devices using the stochastic dual dynamic programming algorithm applied to the mathematical model represented in a scenario tree. We also provide a scheme to use stochastic dual dynamic programming policies in the evaluation of capacity sizing of storage devices for households. Our methodology is applied to a case study consisting of a community of five houses and the results are discussed. The proposed approach is an enabler for the future shared community generation-storage designs in the smart grid environment providing a technical decision-making framework for storage addition, and capacity sizing of storage devices, that allows planners to perform comparisons between the optimal capacity sizing of shared versus individually controlled and owned devices based on net present value calculations. The results obtained from the shared energy management control strategy suggest that by controlling the energy storage devices and the solar PV generation power flow, it is possible not only to improve critical parameters such as electricity purchase costs, electricity peak shaving and solar PV usage on a daily basis but also to reduce the storage capacity requirement. As a result, this tool benefits the homeowner in terms of reducing electricity purchases from the grid and the energy storage installation costs. The tool discussed here can be further expanded to satisfy different goals such as loss minimization, ancillary services, and others to study the effect of coordinated control strategies among shared resources and storages.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apenergy.2018.11.080.

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