Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array

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Xiaohua Wu [a], Xiaosong Hu [b, *], Scott Moura [c], Xiaofeng Yin [a], Volker Pickert [d]

[a] School of Automobile and Transportation, Xihua University, Chengdu, 610039, China
[b] The State Key Laboratory of Mechanical Transmissions, Chongqing University, Chongqing, 400044, China
[c] Energy, Controls, and Applications Laboratory, University of California, Berkeley, USA
[d] School of Electrical and Electronic Engineering, Newcastle University, UK

HIGHLIGHTS

- Markov Chain model of PEV mobility is achieved.
- Conditional probability of trip length is developed.
- Predictive models of home power demand and PV power supply are achieved.
- PEV energy storage availability by SDP is modeled.
- The SDP control can bring significant cost savings for customers.

ARTICLE INFO

ABSTRACT

Energy management strategies are instrumental in the performance and economy of smart homes integrating renewable energy and energy storage. This article focuses on stochastic energy management of a smart home with PEV (plug-in electric vehicle) energy storage and photovoltaic (PV) array. It is motivated by the challenges associated with sustainable energy supplies and the local energy storage opportunity provided by vehicle electrification. This paper seeks to minimize a consumer's energy charges under a time-of-use tariff, while satisfying home power demand and PEV charging requirements, and accommodating the variability of solar power. First, the random-variable models are developed, including Markov Chain model of PEV mobility, as well as predictive models of home power demand and PV power supply. Second, a stochastic optimal control problem is mathematically formulated for managing the power flow among energy sources in the smart home. Finally, based on time-varying electricity price, we systematically examine the performance of the proposed control strategy. As a result, the electric cost is 493.6% less for a Tesla Model S with optimal stochastic dynamic programming (SDP) control relative to the no optimal control case, and it is by 175.89% for a Nissan Leaf.

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1. Introduction

1.1. Motivation

The present energy demand and environmental crisis have been promoting the rapid development of electric vehicles (EVs) and renewable energy including solar rooftop photovoltaic (PV) and wind power [1,2]. However, EVs charging activities and renewable energy generation are always intermittent and volatile. If uncontrolled, a significant impact on the power grid may happen, including performance degradations, overloads, and over-generation, especially when a larger scale distributed generation (DG) unit and EVs are used [3–5]. Reconciling EVs and renewable energy to ensure optimal usage of electric power is very important for the performance and economy of smart grid [6–8]. As a consequence, researchers have recently focused on developing effective management for integrating EVs and renewable energy into house loads and grid, as well as new material and structure of renewable energy considering power conversion efficiency, such as SiO_2 nanoparticles [9], iodide/triiodide-based redox mediator [10],

and photopolymerization of Co(II)/Co(III) used for solar cells [11]. Related to recent attention paid to smart grid vision, smart homes that can optimize energy consumption and lower electricity bills have also gained specific importance. Developing a smart home energe management system (SHEMS) has become a common global priority to support the trend towards a more sustainable and reliable energy supply for smart grid [12]. Hence, this paper focuses on optimal energy management of a smart home with plug-in electric vehicle (PEV) battery energy storage and solar power supply.

1.2. Literature review

The existing literature, e.g., the forgoing work, has presented several optimization methods, such as mixed-integer linear programming (MILP) [13–17], model predictive control (MPC) approach [4,18], rolling horizon strategy [19], and game theory [20], for creating efficient operational schedules or making good consumption and production decisions to smart home energy management. The operation of a smart household that owned a PV, an energy storage system that consisted of a battery bank and also an EV with vehicle to home (V2H) option was considered through solving a MILP in Ref. [13]. A MILP model of the HEM structure was provided to perform a collaborative evaluation of a dynamic pricing based demand response (DR) strategy, a distributed small-scale renewable energy generation system, the V2H capability of an EV together with two-way energy trading of EV (using V2G option) and enenrgy storage system (ESS) in Ref. [14]. An optimal smart household appliances scheduling was established under hourly pricing and peak power-limiting (hard and soft power limitation)-based demand response strategies in Ref. [15], where thermostatically and non-thermostatically controllable loads were explicitly modeled. The optimal operation of a neighborhood of smart households in terms of minimizing the total energy procurement cost was analyzed using MILP by considering bi-directional power flow both at household and neighborhood level in Ref. [16]. A MILP model for techno-economic optimum sizing of additional PV and ESS investment for a DR-based HEM system controlled smart household was provided with the consideration of the notably changing load pattern due to DR activities in Ref. [17]. Renewable integration was considered in Ref. [4], which derived optimal EV charging schedules based on predicted PV output and electricity consumption. A nonlinear predictive energy management method for buildings with PV system and battery storage was presented in Ref. [18], which forecasted house load demand via artificial neural networks. A novel energy management system based on a rolling horizon strategy for a renewables-based microgrid was proposed and implemented, composed of PV panels, two wind turbines, a diesel generator and an energy storage system in Ref. [19]. The impacts of the response capability levels of consumers on the economic integration of distributed PV power in smart homes, and the impacts of PV capacities and battery capacities on consumers power expenses were analyzed using non-cooperation game theoretical power market complementarity model in Ref. [20].

Most of the related literature pursues a smart home technology potential evaluation objective. Few seek a real-time control system that optimizes energy management with an explicit consideration for stochastic home loads, PV generation, and EV mobility patterns. The main challenge of smart home energy management arises from multiple sources of randomness, i.e., PEV mobility, customer power demand, and renewable power generation. Liang et al. [21] provided a comprehensive literature survey on the stochastic modeling and optimization tools for microgrid and demonstrated the effectiveness of such tools.

To minimize consumer's expected power cost, the optimal scheduling algorithms for power consumption with uncertain future price had been derived under stochastic dynamic programming (SDP) [22]. Iverson et al. accounted for probabilities of vehicle departure time and trip duration to formulate a SDP algorithm to optimally charge an EV based on an inhomogeneous Markov chain model [23]. To promote user demand response through optimizing the utilization of wind power generation, the coordinated wind-PEV dispatch problem was also studied in a stochastic framework capturing the uncertainties of wind power generation and statistical PEV driving patterns [24]. A stochastic energy consumption scheduling algorithm with the objective of reducing monetary expenses was featured by modelling the random property of customer energy consumption practices [25]. However, all the foregoing articles focus on the microgrid energy management problem using stochastic optimization, given one and only one random factor: either electric price or PEV mobility, either renewable energy generation or home load. The interactions among various random variables were constantly overlooked. A probability distribution model combining household power consumption, EV home-charging and PV power production was developed using a convolution approach to merge three separate existing probability distribution models in Ref. [26]. Donadee et al. [27] used stochastic models of (i) plug-in and plug-out behavior, (ii) energy required for transportation, and (iii) electric energy prices. These stochastic models were incorporated into an infinite-horizon Markov decision process (MDP) to minimize the sum of electric energy charging costs, driving costs, and the cost of any driver inconvenience. A later study by Ref. [28] constructed a Markov Chain to model random prices and regulation signal and formulated a SDP to optimize the charging and frequency regulation capacity bids of an EV. The previous two studies, however, did not consider integrated PEV charging with building loads and renewable energy.

1.3. Contributions

To surmount the shortcomings of the foregoing studies [29,30], this paper proposes an SDP framework for the optimal energy management of a smart home with PEV energy storage and PV array, considering multiple uncertain variables. Based on real statistical data, Markov Chain models of vehicle trip time and conditional probability of trip length is achieved, as well as predictive models of home load demand and PV power supply. To the best knowledge of the authors, this is the first time study in the literature modelling PEV energy storage availability by incorporating multiple random variables into a SDP control formulation of a single smart home energy management, which is the main novelty of this paper. We can generally conclude that the smart home with PEV energy storage and PV array under such optimal control can bring significant cost savings for customers.

1.4. Outline of paper

The remainder of the paper is arranged as follows. Section 2 details the system model of a smart home. Detailed random variables are described in Section 3. The optimization problem is formulated in Section 4. The case study optimization results are discussed in Section 5, followed by conclusions presented in Section 6.

2. Smart home model development

2.1. Smart home configuration

We consider a smart home with a PEV and solar panels as shown in Fig. 1. The energy management system communicates with home
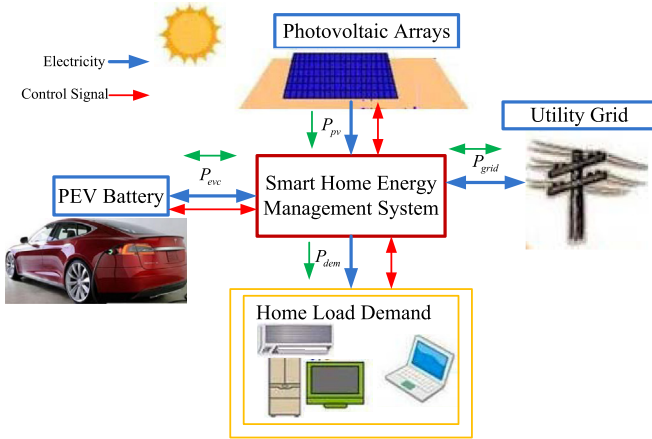
Fig. 1. Structure of smart home with PEV energy storage and PV power supply.

appliances, the electric utility, the PEV and solar panels. We assume the PEV battery is composed of a Li-ion battery pack and is controlled by DC/AC converter in SHEMS. The power electronics are designed to allow both bidirectional and unidirectional power flow. The SHEMS is also used to manage the power flow between the PEV battery, home appliances, PV array and utility grid.

2.2. Historical data analysis

We analyse the PV power supply data and load data from a single family home with PV array and a PEV (Tesla Model S with 85 kW h battery pack) in Santa Rosa, California, USA. Data is collected between 2014-07-01 and 2015-03-31. The time resolution of the data is 1 h. Under uncontrolled charging regime, hourly grid power consumption P_{grid}, PV power generation P_{pv}, PEV charging power P_{ev}, and home load demand P_{dem} are shown in Fig. 2. The hourly home load demand varies from 0.19 kW to 3.99 kW. Except the much higher power consumption in the evening, the home load demand is also large during the day. The hourly PV power supply varies from 0 to 4.08 kW. We can observe that the PV power supply is centralized from 9:00 AM to 5:00 PM. and sometimes exceeds the home power demand. The charging infrastructure is a dual charger
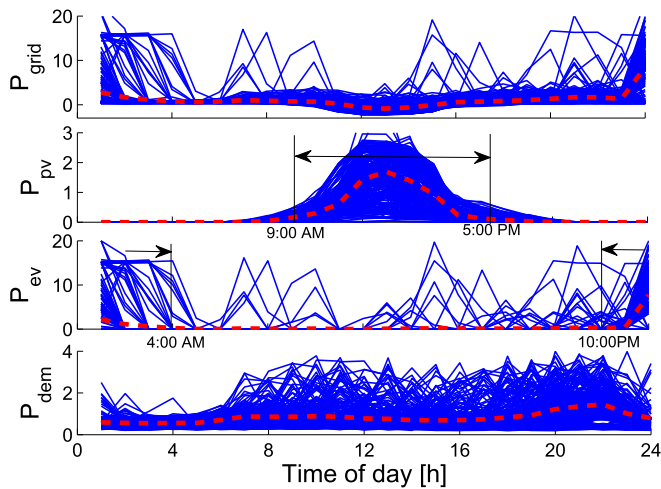
(20 kW) [31], and we can see that most of the PEV battery charging occur from 10:00 PM to 4:00 AM. The hourly grid power varies from −2.28 kW to 23.12 kW. However, the PEV charging power is large and the continuous charging time is relatively short. This PEV charging regime may be harmful for the battery health and grid stability. We try to apply a stochastic optimal control approach to improve the system and synthesize an energy management controller for the home.

2.3. System modeling

Considering the state of PEV, the power balance equation of a smart home with PEV energy storage and PV power supply is

$$P_{grid,k} = S_k P_{evc,k} + P_{dem,k} - P_{pv,k}, \quad k = 0, \ldots, N - 1, \tag{1}$$

$$S_k = \begin{cases} 0 & \text{for } t_d \leq k \leq t_a \\ 1 & \text{otherwise}, \end{cases} \tag{2}$$

where $P_{grid,k}$, $P_{dem,k}$, $P_{evc,k}$ and $P_{pv,k}$ are the electric power from the grid, the power demand of the home, the PEV battery charger power, and the power supply of the PV array, respectively. Variable k is the time index, and S_k denotes the PEV state at time k, i.e., plugged-in ($S_k=1$) or plugged-out ($S_k=0$). The variables t_d and t_a are the plugging-out time and plugging-in time, respectively. In this paper we assume the PEV plugs-out and plugs-in once a day. The controller also must maintain PEV battery energy and charger power within simple bounds,

$$E^{min} \leq E_k \leq E^{max}, \quad k = 0, \ldots, N, \tag{3}$$

$$P^{min} \leq P_{evc,k} \leq P^{max}, \quad k = 0, \ldots, N - 1, \tag{4}$$

where E_k is the energy of PEV battery. E^{min} and E^{max} are the PEV battery's minimal energy and maximal energy, respectively. P^{min} and P^{max} are the PEV battery charger's minimal power and maximal power, respectively. The dynamics of the battery are given by the following equation:

$$E_{k+1} = E_k + \Delta t \left(P_{evc,k} - \eta |P_{evc,k}| \right), \quad k = 0, \ldots, N - 1, \tag{5}$$

$$E_0 = E_{init}, \tag{6}$$

where Δt, η and E_{init} are the time-step, lost efficiency of PEV charger and initial PEV battery energy, respectively. The charge power is assumed to be positive, by convention. Considering battery's expensive price and limited lifetime, as well as the grid power quality, the power from smart home to the grid should be limited as follows

$$P_{grid,k} \geq -P_{grid}^{max}, \tag{7}$$

where $P_{grid}^{max} \geq 0$ is the maximal power that can be provided to the grid. The power from the smart home to the grid is assumed to be negative, by convention. However, selling power back to the grid can cause voltage increases in the distribution lines and reverse power flows. This can violate voltage constraints - a topic not addressed in this paper. In this paper, P_{grid}^{max} is limited to be less than 3 kW.

3. Stochastic variables model development

A major challenge for this energy management system is to deal with uncertainty in the five parameters: PEV plug-in time, plug-out

Fig. 2. Statistical hourly power (kW) data for Grid power, PV power supply, PEV battery charger power, and home load demand on each day (blue) and average (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

time, charge required for mobility, PV power supply and home load demand [32]. Given the statistics about the uncertain parameters, this section describes the Markov chain [33,34] models of PEV mobility and predictive models of PV power generation and home load demand.

3.1. PEV trip time model

Considering the PEV to be plugged-in ($S_k = 1$) or plugged-out ($S_k = 0$) at time k, we model the dynamics of PEV trip time by a Markov chain. We assume the quantity $p(k)$ is the transition probability of plugging-out and $q(k)$ is the transition probability of plugging-in. Then the Markov chain can be written as

$$
\begin{aligned}
P_{ij,k} &= \Pr[S_{k+1} = j | S_k = i, k], \qquad i,j \in \{0,1\}^2, \\
P_{10,k} &= \Pr[S_{k+1} = 0 | S_k = 1, k] = p(k), \\
P_{11,k} &= \Pr[S_{k+1} = 1 | S_k = 1, k] = 1 - p(k), \\
P_{01,k} &= \Pr[S_{k+1} = 1 | S_k = 0, k] = q(k), \\
P_{00,k} &= \Pr[S_{k+1} = 0 | S_k = 0, k] = 1 - q(k).
\end{aligned}
\tag{8}
$$

The start time of outgoing trips from home (or residential area) is called the plugging-out time, and the plugging-in time is the end of the last return trip. In order to study the randomness of trip time, we investigated 10 individuals daily driving schedules over 3197 person-work days (10 individuals work in a university office in Chengdu, China and their work hours are from 8:30 AM to 5:30 PM). According to the analysis of the daily driving schedules, the temporal distribution of vehicle plugging-in and plugging-out times is shown in Fig. 3-(a). The plugging-out time distribution is concentrated around 6:45–8:30 AM, and corresponds to morning commutes. The mean value of the plugging-out time is 7:40 AM (7.66 h), and the standard deviation (std) is 0.57 h. The plugging-in time distribution shows the highest peak around 5:30–8:00 PM, the mean value is 6:38 PM (18.64 h), and the std is 0.89 h.

3.2. PEV battery energy model at plugging-in time

The randomness of PEV battery energy at plugging-in time is affected by many factors, including the PEV battery energy at plugging-out time, driving distance, driving styles, and more [35]. Here we only consider the effect of daily trip distance to compute the PEV battery energy at plugging-in time as

$$
E_{pi} = \begin{cases} E^{\min}, & \text{if } E_{po} - \dfrac{d}{E_{ff}} \leq E^{\min}, \\[2mm] E_{po} - \dfrac{d}{E_{ff}}, & \text{otherwise,} \end{cases}
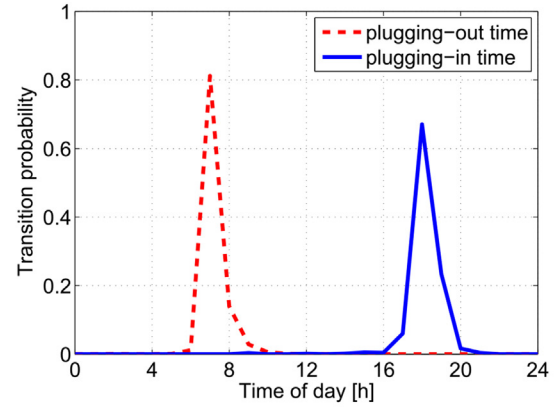\tag{9}
$$

where E_{pi} is the PEV battery energy at plugging-in time, E_{po} is the PEV battery energy at plugging-out time, d is the trip distance, and E_{ff} is the overall electric drive efficiency which we assume equal to 6.7 km/kWh [36]. If given E_{po} and d, then E_{pi} can be computed. Note that E_{pi} is lower-bounded by $E^{\min}$, which prevents battery depletion. Consequently, we can compute the conditional probability distribution of E_{pi} according to
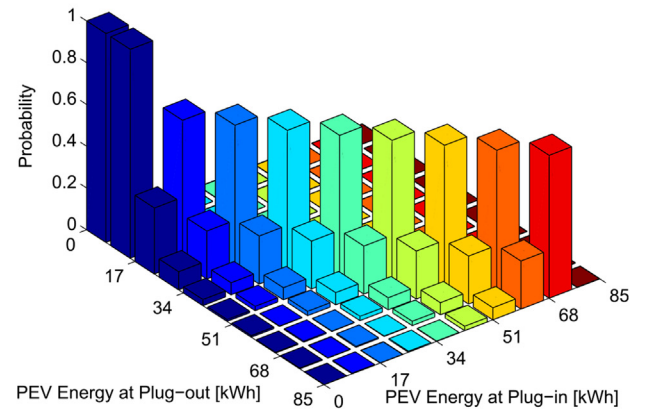
$$
m_{hg} = Pr[E_{pi} = E_h | E_{po} = E_g],
\tag{10}
$$

where E_h and E_g are sample values from the discretized set of feasible PEV battery energy values,

$$
E_h, E_g \in S = \left\{ E_i = E^{\min} + i \cdot \Delta E \mid i \in \mathbb{N}, \ E^{\min} \leq E_i \leq E^{\max} \right\}.
\tag{11}
$$

The quantity m_{hg} is the probability that plugging-in energy

(a) Distribution of plugging-in and plugging-out times.

(b) Conditional probabilities of plugging-in PEV energy E_{pi}, given the plugging-out PEV energy E_{po} [37].

Fig. 3. Trip time and plugging-in PEV energy.

$E_{pi} = E_h$, given plugging-out energy $E_{po} = E_g$. In the light of the statistical daily trip length distribution from 2009 US National Household Travel Survey (NHTS) [37], the conditional probabilities for the plugging-in energy E_{pi}, given the plugging-out energy E_{po} are shown in Fig. 3-(b).

3.3. PV power forecast

The literature provides a great deal of methods to model the PV power and improve the PV efficiency [38–40], such as the maximum power point tracking (MPPT) algorithm. It's difficult to forecast the PV power generation because of the uncertainty of solar flux and air temperature [18]. In this paper, a radial basis function neural network (RBF-NN) forecast algorithm is utilized to forecast day-ahead (future 24 h) PV power supply. RBF-NN is selected because it captures the nonlinear input-output relations of PV power supply and achieves reasonable forecast accuracy. First, we assume that day-ahead air temperature information is directly provided by weather forecast services. The air temperature and time of day are selected as exogenous input to the RBF-NN model, together with the endogenous input, the historical PV power generation. Thus, the input of the RBF-NN is designed as

$$X = [T_a \quad T_d \quad P_h]^T, \tag{12}$$

where T_a is the day-ahead air temperature, T_d is the day-ahead time of day and P_h is the historical PV power generation.
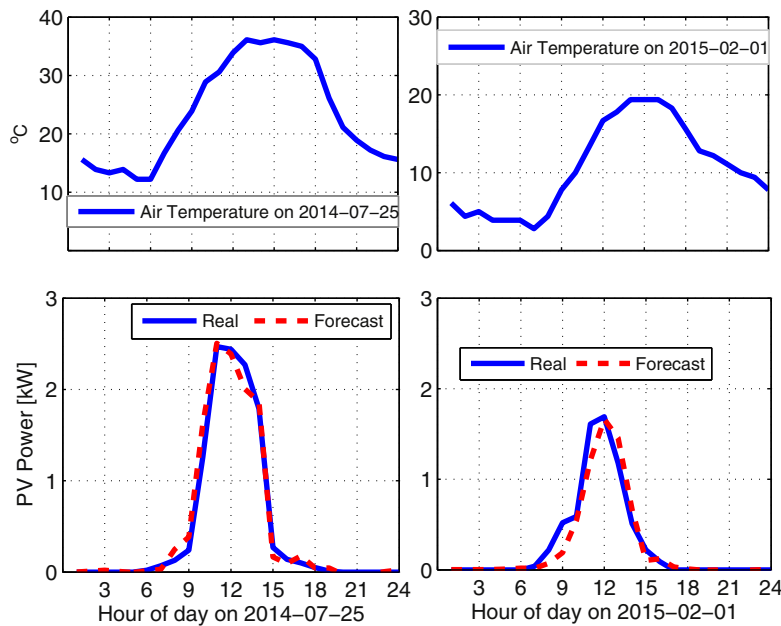
We analyse the PV power supply data from the Santa Rosa family home to forecast the PV power. PV power data is collected between 2013-07-01 and 2015-03-31 and comes from Solar City [41]. The first year of data is used for the network training, and the remaining data is used for validation and comparison. Fig. 4-(a) shows the result for 2 different days. The former one is with a warm temperature in summer, and the latter one is with a cold temperature in winter. Fig. 4-(a) exhibits the RBF-NN's accurate ability to forecast the PV power supply.

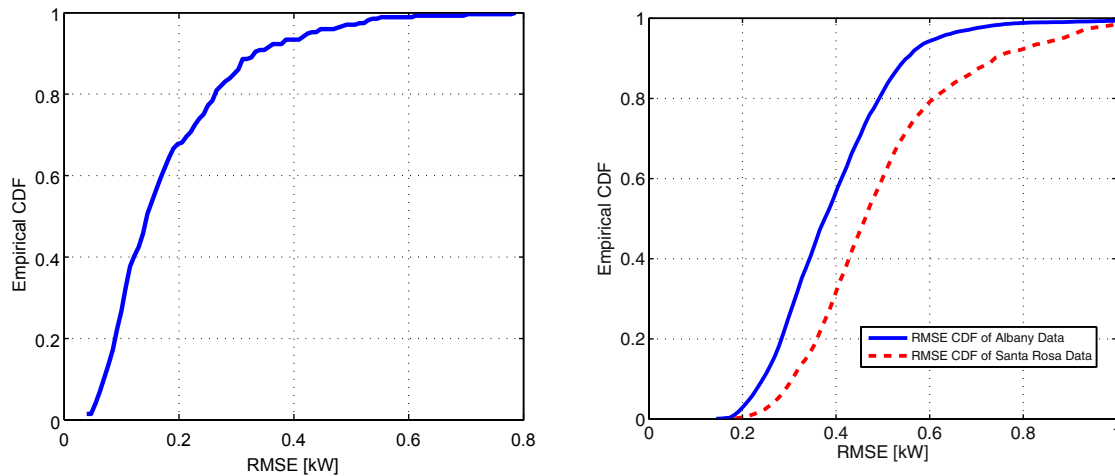The remaining data are used for validation, which in total contains 274 forecast periods. Every day only forecasts once at the start of the day (00:00). The root mean squared error (RMSE) for each process is calculated, and the empirical cumulative distribution function (CDF) of all the RMSEs are shown in Fig. 4-(b). It can be seen that 80% of the forecast RMSEs are below 9% (0.27 kW/3 kW) of the rated PV capacity. The RBF-NN model is able to maintain the forecast error within an acceptable range.

3.4. Home load demand forecast

The literature is rich with machine learning and stochastic modelling approaches for home load demand [42,43]. In this paper, similar as the PV power supply, we use the RBF-NN to forecast the day-ahead home load demand. The air temperature, future day of week, and time of day are selected as exogenous input to the RBF-NN model, together with the endogenous input, the historical home load demand. The validation data is real electricity

(a) Forecast examples and the air temperature.

(b) Empirical CDF for forecast RMSE of PV power supply data

(c) Empirical CDF for forecast RMSE of home load demand data

Fig. 4. Forecast result.

consumption data collected from two houses located in Santa Rosa (2014-07-01 to 2015-3-31) and Albany, CA (2013-07-01 to 2015-06-30). The first half data is used for network training, and the second half data is used for validation and comparison. The RMSE for each process is calculated, and the empirical CDF of all the RMSEs are demonstrated in Fig. 4-(c). It can be seen that 80% of the forecast RMSEs are below 0.60 kW and 0.49 kW in Santa Rosa and Albany data, respectively.

4. Optimization problem formulation

This section presents the SDP approach used for solving the optimal power management problem for smart home. The objective is to manage power flow to minimize energy cost, which includes household electric power demand, PV power supply, PEV battery charging and discharging. Other objectives are directly applicable as well, e.g. minimize marginal power plant carbon emissions, battery degradation, shifting grid load, etc..

Armed with the Markov chain modelling framework to incorporate statistics of the random processes (e.g. plugging-out time, plugging-in time, PEV battery energy at plugging-in time) and forecasting day-ahead PV power supply $\widehat{P}_{pv,k}$ and home load demand $\widehat{P}_{dem,k}$, we can now formulate an SDP. The block diagram of the optimal controller is shown in Fig. 5. We use the PEV battery energy E_k as the state variable and the PEV battery charger power $P_{evc,k}$ as the control variable. With the stochastic system characterized by the pair $\{S_k, E_{pi}\}$, we formalize the finite-time SDP [44] as

$$\min_{P_{evc,k}, E_k, S_k} \mathbb{E} \sum_{k=0}^{N-1} c_k \Delta t \left(S_k P_{evc,k} + \widehat{P}_{dem,k} - \widehat{P}_{pv,k} \right) \quad (13)$$
s.t.

$$E_{k+1} = \begin{cases} E_k, S_k = 0 \to S_{k+1} = 0 \\ \mathrm{Proj}[E_{pi}]_{E^{\min}}^{E^{\max}}, S_k = 0 \to S_{k+1} = 1 \\ E_k + \Delta t \left(P_{evc,k} - \eta |P_{evc,k}| \right), S_k = 1 \to S_{k+1} = 0 \\ E_k + \Delta t \left(P_{evc,k} - \eta |P_{evc,k}| \right), S_k = 1 \to S_{k+1} = 1. \end{cases} \quad (14)$$

Eqns(1)–(11) are constraints of the optimization problem, and in Eq. (13) c_k is the time-varying electricity price [cents/kWh].
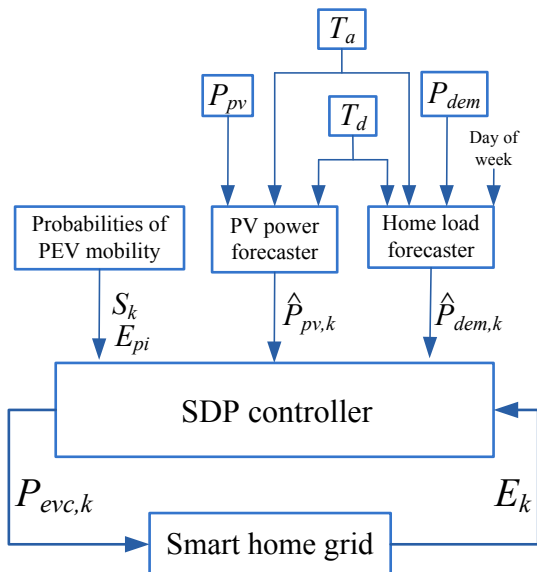

Fig. 5. Block diagram of stochastic controller.

5. Results & discussion

This section analyzes the properties of the proposed energy management system by comparing its performance with the uncontrolled charging regime. All the simulations are run on a PC with a 2.5 GHz Intel Core i5-2450M CPU and 4 GB of internal memory. When the proposed SDP is implemented in the real word, the optimal charging policy needs to be optimized by backward recursion every time the PEV plugs in. The SDP computational time is 4.21 s with 25 h look ahead horizon. The SDP is computed offline from the smart home operation, and therefore real-time applicability is not an issue for the SDP calculations themselves. The resulting control law takes the form of a lookup table, which is trivially simple to implement in real-time.
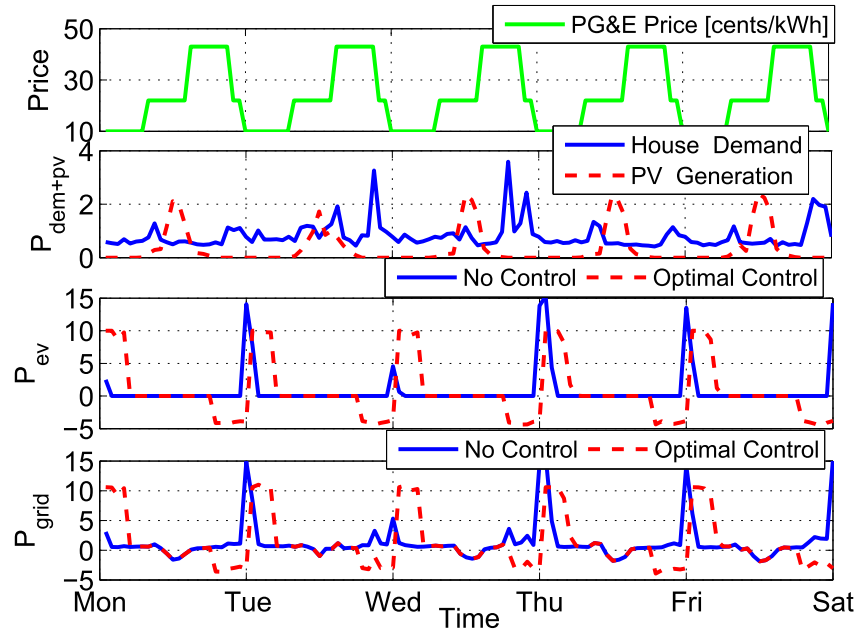
The time-varying electric price signal and transition probabilities of trip time and length, day-ahead predicted PV power generation and home load demand are the inputs of the SDP control algorithm. The time-varying electric price signals are taken from the PG&E (Pacific Gas and Electric Company) EV plan [45]. We assume the PEV charges only at home, and that the available charging infrastructure is a Tesla single charger (10 kW) [31] to limit the maximal charger power. Table 1 lists the parameter values used for these optimization studies. All the simulations are run on a PC with a 2.5 GHz Intel Core i5-2450M CPU and 4 GB of internal memory.

We assume the PEV is driven between work and home with 12 kWh battery energy demand (daily average PEV charging energy), pluging-out at 7:00 AM-8:00 AM, and plugging-in at 6:00 PM-7:00 PM. The results for arbitrary five weekdays (2015-03-23 to 2015-03-27) are shown in Fig. 6-(a). When optimally controlled, the PEV charges from the grid when the electric price is low and discharges to the grid when the electric price is high. At the same time, the total power demand from the grid is reduced when grid load is high, and is increased around midnight. Finally, this results in shifting the overall house loads. The PEV always has enough energy for driving in the morning. The energy of PEV battery varies from 38 kWh to 76 kWh (state of charge SOC from 0.45 to 0.89), and remains in secure bounds for the battery health. The hourly energy cost from 2015-03-23 (Mon) to 2015-03-27 (Fri) is shown in Fig. 6-(b).
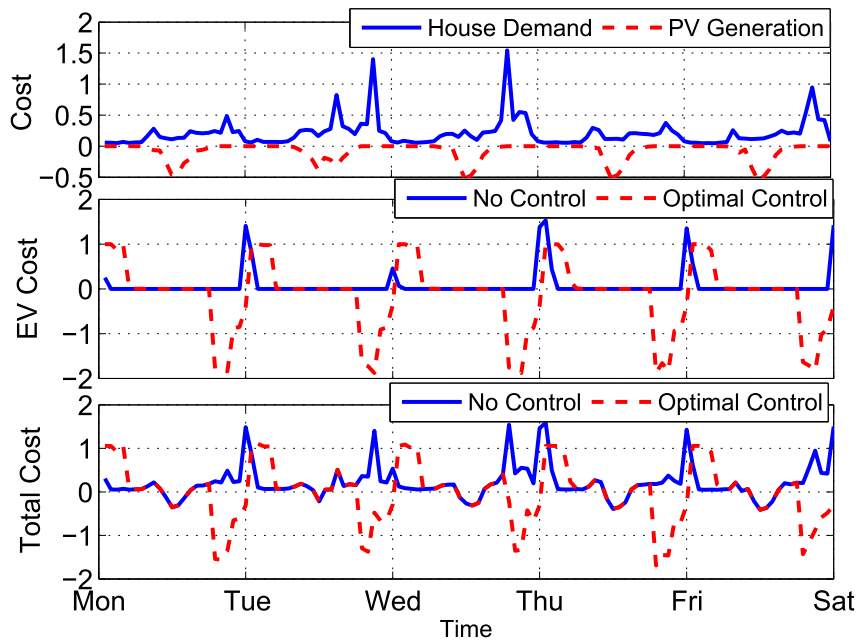
To demonstrate the potential financial benefits of the smart home microgrids, the profits analysis for different arbitrary weekdays are summarized by Table 2, which examines the electric cost from 2015-03-23 (Mon) to 2015-03-27 (Fri) and 2014-12-01 (Mon) to 2014-12-05 (Fri). From 2015 to 03-23 (Mon) to 2015-03-27 (Fri), the total home energy cost and the solar generation profits are respectively 24.91 USD and 9.90 USD. In the uncontrolled case, the PEV charging cost is 9.64 USD and the total energy cost is 24.65 USD. This can be compared with the optimal control case where the PEV charging cost is −17.94 USD and total energy cost is −2.92 USD.

Table 1
System parameters.

Parameter description	Symbol	Value	Unit
PEV Battery Energy Capacity	Q_{eap}	85	kWh
Maximum Battery Energy	$E^{\max}$	76.5	kWh
Minimum Battery Energy	$E^{\min}$	17	kWh
Maximum Charging Power	$P_{bat}^{\max}$	10	kW
Minimum Discharging Power	$P_{bat}^{\min}$	−10	kW
Maximum Power to grid	$P_{grid}^{\max}$	3	kW
Lost efficiency of PEV charger	η	0.05	
Energy for day driving	P_{driv}	12	kWh
Pluging-out time	t_d	7:00 a.m.−8:00 a.m.	
Pluging-in time	t_a	6:00 p.m.−7:00 p.m.	
Time Step	Δt	1	hour

(a) Energy management result (kW)

(b) Energy cost (USD)

Fig. 6. From 2015-03-23 (Mon) to 2015-03-27 (Fri).

Table 2
Electricity cost (USD).

	2015-03-23 to 2015-03-27		2014-12-01 to 2014-12-05	
	No control	Optimal control	No control	Optimal control
Home Load	24.91	24.91	23.93	23.93
PV Profits	9.90	9.90	3.28	3.28
PEV	9.64	−17.94	3.70	−17.53
Total	24.65	−2.92	24.35	3.11

The average daily energy cost is reduced by 5.51 USD when it is optimally controlled. From 2014-12-01 (Mon) to 2014-12-05 (Fri), the total home energy cost and the solar generation profits are respectively 23.93 USD and 3.28 USD. In the uncontrolled case, the PEV charging cost is 3.70 USD and the total energy cost is 24.35 USD. This can be compared with the optimal control case where the PEV charging cost is −17.53 USD and total energy cost is 3.11 USD. The average daily energy cost is reduced by 4.25 USD when it is optimally controlled. This shows that optimal control of PEVs can save significant amount of money.
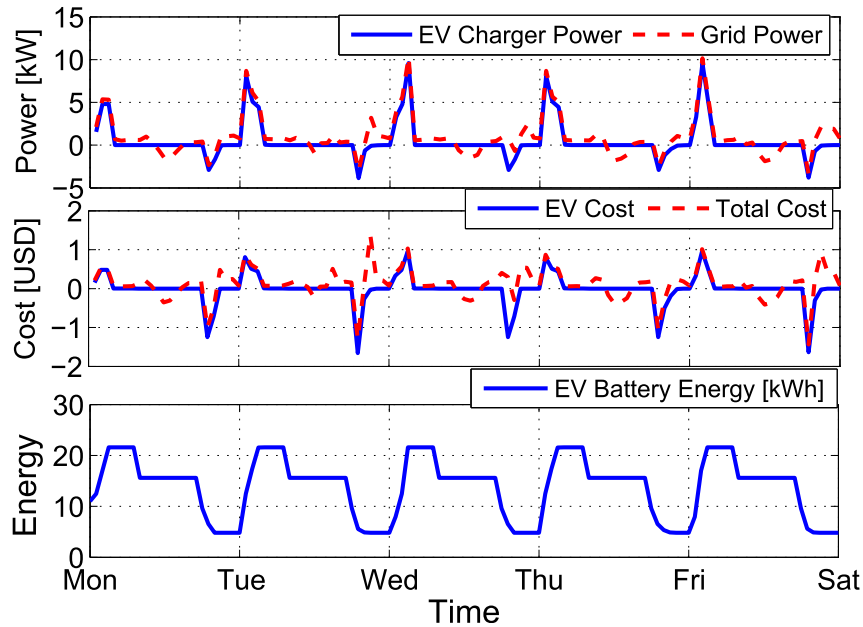
Fig. 7. Simulation results for Nissan Leaf.

Based on the parameters of Table 1, a different model of EV (Nissan Leaf, the battery energy capacity is 24 kWh) is adopted. The results for arbitrary five weekdays (2015-03-23 to 2015-03-27) are shown in Fig. 7. If the user has a Nissan Leaf, the PEV charging cost is −1.62 USD. The average daily charging cost is −0.324 USD for Leaf and it is −3.59 USD for Tesla Model S. This shows that the PEV with larger energy capacity can save significant amount of money.

To demonstrate the potential financial benefits of PEV and PV to smart home microgrids, we consider the annual profits for different models of PEV. The statistical hourly power data for home load demand, PV power supply, and Grid power on each day in one year, as shown in Fig. 8, are used. The mean value of daily house electric power demand cost is 1.47 USD/day, and the total yearly cost is 535.23 USD. The mean value of daily PV power generation profits is 1.87 USD, and the total yearly profits is 683.31 USD. We assume the PEV daily power need is 12 kWh. Here, we analyse the financial benefits by comparing three different PEV models. For Case 1, the user has a PEV without optimal control, the total daily PEV charging cost is at least 1.2 USD (10 cents/kWh); for Case 2, the user has a Tesla Model S (85 kWh battery pack) with the proposed SDP optimal control; for Case 3, the user has a Nissan Leaf (24 kWh battery pack) with the proposed SDP optimal control. The analysis summarized by Table 3 examines the annual electric cost with different PEV models.
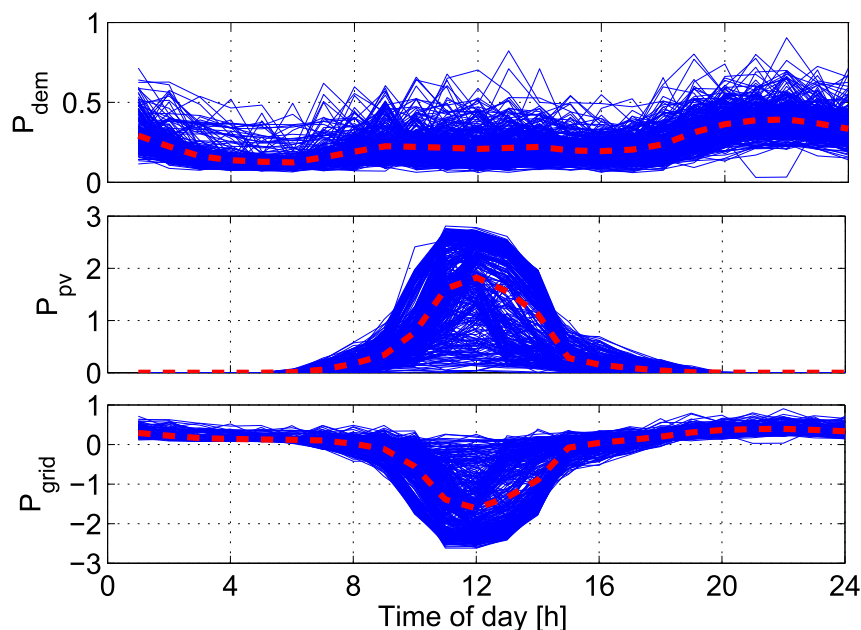

Fig. 8. Statistical hourly power (kW) data for home load demand, PV power supply, and Grid power on each day (blue) and average (red). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 3
Annual electric cost (USD).

	Year total	Daily average
House Demand	535.23	1.47
PV Generation	−683.31	−1.87
PEV with No Control	438	1.2
Grid with No Control	289.92	0.79
Model S with SDP	−993.01	−2.72
Grid with Model S	−1141.1	−3.13
Leaf with SDP	−71.95	−0.20
Grid with Leaf	−220.03	−0.60

It can be seen, without optimal control, the mean value of the daily and the total yearly electricity costs are 0.79 USD/day and 289.92 USD, respectively. On the other hand, with the proposed optimal control and Tesla Model S, the mean value of the daily and the total yearly electricity costs are −3.13 USD/day and −1141.1 USD, respectively. Similarly, with the proposed optimal control and Nissan Leaf, the mean value of the daily and the total yearly electricity costs are −0.6 USD/day and −220.03 USD, respectively. Thus, over one year period, the total electricity cost for Tesla Model S and Nissan Leaf with SDP control are 493.6% and 175.89% less than those without optimal control, respectively. The energy management strategy is exploiting price arbitrage by selling electricity to the grid when it is of high price and buying electricity from the grid when it is of low price.

6. Conclusion

This paper develops a stochastic optimization framework for energy management of a smart home with PEV energy storage and PV power supply. An SDP problem is formulated to optimize the electric power allocation in the PEV battery, home load demand, PV power supply and utility grid. The strategy explicitly takes into account probability distributions of trip time and trip length, and prediction of home load demand and PV power production. We analyse the potential cost savings of the smart home with PEV energy storage and PV power supply under SDP control, compared to the uncontrolled PEV charging regime. We find that SDP control can bring significant cost savings for customers and load shifting for the grid. From our simulation study, we concluded that over one year period, the total electricity cost with our proposed SDP optimal control for Tesla Model S (85 kWh battery pack) and Nissan Leaf (24 kWh battery pack) are 493.6% and 175.89% less than those without the optimal control, respectively.

To the best knowledge of the authors, this is the first study in the literature modelling PEV energy storage availability by incorporating multiple random variables into a SDP control formulation of a single smart home energy management, which is the main novelty of this paper. Future work could incorporate multi-objective optimization such as improving the battery life, or supplying frequency regulation and spinning reserves. This paper only considers a single home, future work will look at larger microgrids, which include a larger scale DG unit and EVs.

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