

Optimal Integration of a Hybrid Solar-Battery Power Source into Smart Home Nanogrid with Plug-In Electric Vehicle

Xiaohua Wu^a, Xiaosong Hu^{b,c,**}, Yanqiong Teng^a, Shide Qian^d, Rui Cheng^a

^a*School of Automobile and Transportation, Xihua University, Chengdu, 610039, China*

^b*State Key Laboratory of Mechanical Transmissions, Department of Automotive Engineering, Chongqing University, Chongqing, 400044, China*

^c*Advanced Vehicle Engineering Centre, Cranfield University, Cranfield, MK43 0AL, UK*

^d*Beijing Benz Automotive Co.Ltd, Beijing 100176, China*

Abstract

Hybrid solar-battery power source is essential in the nexus of plug-in electric vehicle (PEV), renewables, and smart building. This paper devises an optimization framework for efficient energy management and components sizing of a single smart home with home battery, PEV, and photovoltaic (PV) arrays. We seek to maximize the home economy, while satisfying home power demand and PEV driving. Based on the structure and system models of the smart home nanogrid, a convex programming (CP) problem is formulated to rapidly and efficiently optimize both the control decision and parameters of the home battery energy storage system (BESS). Considering different time horizons of optimization, home BESS prices, types and control modes of PEVs, the parameters of home BESS and electric cost are systematically investigated. Based on the developed CP control law in home to vehicle (H2V) mode and vehicle to home (V2H) mode, the home with BESS does not buy electric energy from the grid during the electric price's peak periods.

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**Corresponding author (X.Wu and X. Hu equally contributed to this research work.)

Email address: xiaosonghu@ieee.org (Xiaosong Hu)

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1. Introduction

1.1. Motivation

The present energy demand and environmental crisis has been promoting the rapid development of electric vehicles (EVs) and renewables [1, 2]. However, EVs charging activities and some renewable energy generation, such as solar and wind power, are always intermittent and volatile. Reconciling EVs and renewables to ensure optimal usage of electric power is critical for the performance and economy of smart grid [3, 4], especially when larger-scale distributed generation (DG) units and EVs are deployed [5]. As a consequence, researchers have recently focused on developing effective management and sizing techniques for integrating EVs and renewables into house loads and the grid. New material and structure of renewables devices were also reported. For example, a newly designed microfluidic architecture with a hyperflexible siliconic matrix is proposed in [6], as a polymeric cage in dye-sensitized solar cell (DSSC). A photocurable polymeric membrane is employed as quasi-solid electrolyte for both the electrochromic device and the DSSC in [7]. Moreover, a flexible integrated energy harvesting and storage system is devised in [8] by coupling DSSC and an electrical double layer supercapacitor.

Related to the recent attention given to smart grid vision, smart home nanogrids that can optimize energy consumption and lower electricity bills have also gained particular importance. The results in [9] have comprehensively demonstrated the second-life battery energy storage's performance in solar charging, home load following, and utility demand side management for a single family home. Developing a smart home energy management system (SHEMS) and component sizing method has become a common global priority to support the trend toward a more sustainable energy supply for smart grid. One of the

27 key features of smart home nanogrid is the SHEMS that intelligently controls
28 household loads through an association between smart meters, smart appliances,
29 EVs, and home power generation and storage, etc. Besides, power source dimen-
30 sion is another important factor. Hence, this paper focuses on optimal energy
31 management and sizing of a smart home nanogrid with home battery energy
32 storage system (BESS), plug-in electric vehicle (PEV), and potovoltaic (PV)
33 power supply.

34 1.2. Literature review

35 There is a rich literature for optimized home energy management (HEM)
36 approaches, which can be generally categorized into mixed-integer linear pro-
37 gramming (MILP) [10], geometric program [11], model predictive control (MPC)
38 [12], dynamic programming (DP) [13], stochastic dynamic programming (SDP)
39 [14]. The optimal operation of a smart household with a PV, a home battery
40 bank, and an EV with vehicle to home (V2H) option is considered through solv-
41 ing a MILP in [15]. A MILP model of the HEM structure is established in [16]
42 to investigate a joint evaluation of a dynamic pricing and peak power limiting
43 based demand response (DR) strategy, with a bi-directional utilization of EV
44 and energy storage system. An optimal day-ahead household appliances schedul-
45 ing is developed in [17] under hourly pricing and peak power-limiting based DR
46 strategies, where thermostatically and non-thermostatically controllable loads
47 are explicitly modeled using MILP. In addition, the optimal operation of a
48 smart neighborhood, in terms of minimizing the total energy procurement cost,
49 is analyzed using MILP by considering all possible bi-directional power flows in
50 [18]. A MILP model of home energy management system (HEMS), as well as
51 a wavelet transform (WT)-artificial neural network (ANN) forecasting of resi-
52 dential loads, is described in [19] for different price signals. A MILP-based DR
53 strategy with end-user comfort violation minimization is synthesized for residen-
54 tial heating, ventilation, and air conditioning (HVAC) units in [20]. Considering
55 DR, sizing of PV and energy storage system applied in smart households is as-
56 sessed with HEM modeling in a MILP framework in [21]. It is clear that MILP

57 has been widely adopted for either creating efficient operational schedules for
58 HEM or sizing of component. However, few studies exploring HEM MILP mod-
59 els considered optimal component size and control strategy simultaneously. A
60 new effective tool, convex programming (CP), which can rapidly and efficiently
61 optimize both management strategy and parameters, has also been applied by
62 some researchers in the energy management field.

63 Due to the significant advantage of CP in computational efficiency, CP is
64 gaining growing popularity in energy management of energy systems. The prob-
65 lem of integrating residential PV power generation and storage systems into the
66 smart grid is addressed in [22] for simultaneous peak power shaving and total
67 electricity cost minimization over a billing period, where a convex optimization
68 problem is formulated and solved. A renewable energy buying-back scheme
69 with dynamic pricing to achieve the goal of energy efficiency for smart grids is
70 modeled as a convex problem in [23], which can significantly reduce peak time
71 loading and efficiently balance system energy distribution. Based on convex
72 objectives and constraints of a grid-tied PV storage system, an optimization
73 problem to obtain a control schedule for storage units is solved by CVX in [24].
74 Based on the objective of reduction of the substation transformer losses, cost
75 saving of energy delivered from the grid, and reduction of the impact on the
76 life-cycle cost of the BESS, a convex optimization approach to schedule charg-
77 ing and discharging of the lithium-ion-based BESS in a distribution feeder with
78 penetration of renewables is discussed in [25]. To assess optimal residential DR
79 in a distribution network, a CP problem is formulated to minimize electricity
80 payment and waiting time under real-time pricing for a multiagent system in
81 [26]. A novel convex quadratic objective function for active power management
82 of plug-in hybrid electric vehicles (PHEVs) is proposed in [27] for minimizing
83 energy loss of microgrid, where the convexity of the proposed method leads to
84 a fast, precise solution facilitating real-time dispatch. Given the price informa-
85 tion, a versatile CP framework for the load management of various household
86 appliances, in order to support DR through energy management system (EMS)
87 in a single smart home, is constructed in [28]. To perform effective storage

88 control based on the predictions of PV power generation and load power con-
89 sumption, [29] splits a residential storage control algorithm into two tiers: the
90 global control tier and the local control tier. The global tier, which is performed
91 to globally plan future discharging/charging schemes of the storage system, is
92 formulated and solved by convex optimization at each decision epoch. It is also
93 mentioned in [29] that finding the optimal sizes of the PV module and storage
94 module with a given budget is possible, but not elaborated.

95 A number of efforts **has** probed energy management of smart grid with renew-
96 ables. Few studies, however, consider optimal component size and control strat-
97 egy simultaneously. CP has been successfully applied to simultaneously optimize
98 the component size and energy controller for hybrid vehicles [30, 31, 32, 33]. In
99 [31], for example, the optimal sizes of the battery pack and fuel cell system, as
100 well as power management strategy, are optimally determined by CP. In this
101 paper, CP is, for the first time, extended to rapidly and efficiently optimize both
102 HEM strategy and sizes of home BESS of a single smart home with both PEV
103 and PV arrays.

104 1.3. Contributions

105 To overcome the downsides of the previous studies, this paper delivers three
106 key contributions to the literature. First, CP is leveraged to rapidly and effi-
107 ciently optimize both the control decision and parameters of the home BESS
108 in the smart home with PEV and PV arrays. **To the best knowledge of the**
109 **authors, this is the first study on the CP-driven joint optimization of control**
110 **strategy and component size of the home BESS with the participation of PEV**
111 **and PV arrays.** Second, based on different time horizons of optimization, home
112 BESS prices, types and control modes of PEV, we attain the optimal parame-
113 ters of the home BESS and electric cost. In contrast to the total electric cost
114 of a home without home BESS, the usefulness of home battery energy storage
115 to increase the home economy is systematically evaluated. Finally, using the CP
116 control law in home to vehicle (H2V) mode and vehicle to home (V2H) mode
117 demonstrates that the home with BESS does not buy electric energy from the

118 grid during the peak periods of electric tariff.

119 1.4. Outline of paper

120 The remainder of the paper proceeds as follows. Section 2 details the system
121 structure and models of the smart home nanogrid. The CP problem is formalized
122 in Section 3. The optimization results are discussed in Section 4, followed by
123 conclusions summarized in Section 5.

124 2. Structure and models

125 2.1. Smart home nanogrid structure

126 We consider a single smart home as shown in Fig. 1 [34], including a PEV
127 battery, solar panels, a home BESS, home equipments, the utility grid, and a
128 SHEMS. The SHEMS communicates with home battery management system
129 (BMS), home appliances, the PEV BMS, and solar panels. The PEV battery is
130 designed to allow both bidirectional and unidirectional power flow. The home
131 battery is designed to allow bidirectional power flow. The SHEMS is also utilized
132 to manage the power flow among the PEV battery, home appliances, PV arrays,
133 the home battery, and the utility grid.

134 2.2. System model

The power balance equation of the smart home nanogrid is

$$P_{grid,k} = P_{dem,k} + P_{b,k} + P_{evc,k}S_k - P_{pv,k}, \quad k = 0, \dots, N - 1, \quad (1)$$

$$0 \leq P_{grid,k} \leq P_{grid}^{\max} \quad (2)$$

$$S_k = \begin{cases} 0 & \text{for } t_d \leq k \leq t_a \\ 1 & \text{otherwise,} \end{cases} \quad (3)$$

135 where we assume $P_{grid,k} \geq 0$, which means that the house is not permitted to
136 supply power to the grid [12]. Variable S_k denotes the PEV state at time k , i.e.,

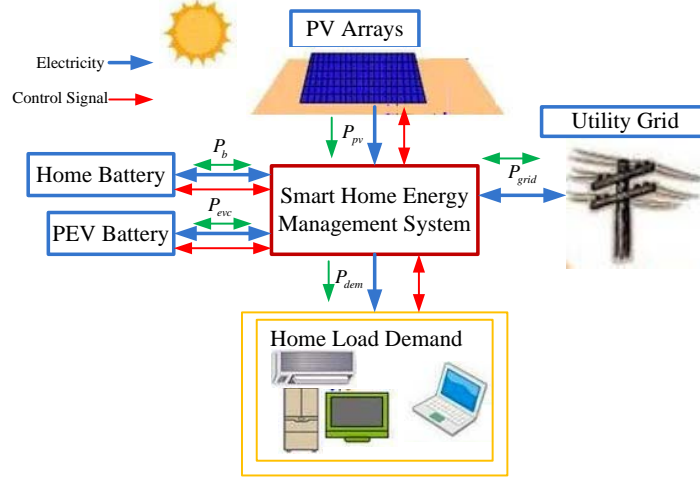


Figure 1: Structure of smart home nanogrid with a PEV and PV arrays [34].

137 plugged-in ($S_k = 1$) or plugged-out ($S_k = 0$) [34, 35]. In this work, we assume
 138 that the PEV plugs-out and plugs-in once a day.

The controller also must maintain PEV battery energy and power within simple bounds [36]. The dynamics and constraints of the PEV battery are given by

$$E_{ev,k+1} = E_{ev,k} + \Delta t(P_{evc,k} - \eta_{evc}|P_{evc,k}|), \quad k = 0, \dots, N-1, \quad (4)$$

$$E_{ev,0} = E_{ev,init}, \quad (5)$$

$$E_{ev}^{plug-out} = SOC_{ev}^{\max} Q_{ev,eap}, \quad (6)$$

$$E_{ev}^{plug-in} = SOC_{ev}^{\max} Q_{ev,eap} - E_{dr}, \quad (7)$$

$$E_{dr} = 0.4Q_{evc,eap}, \quad k = 0, \dots, N, \quad (8)$$

$$Q_{evc,eap} SOC_{ev}^{\min} \leq E_{ev,k} \leq Q_{evc,eap} SOC_{ev}^{\max}, \quad k = 0, \dots, N, \quad (9)$$

$$P_{evc}^{\min} \leq P_{evc,k} \leq P_{evc}^{\max}, \quad k = 0, \dots, N-1, \quad (10)$$

139 where we assume E_{dr} is $0.4Q_{evc,eap}$ [37], and the charge power of the PEV
 140 battery is positive, by convention.

Likewise, the controller also must maintain home battery energy and power

within allowable bounds, and its dynamics are depicted by

$$E_{b,k+1} = E_{b,k} + \Delta t(P_{b,k} - \eta_b |P_{b,k}|), \quad k = 0, \dots, N - 1, \quad (11)$$

$$E_{b,0} = E_{b,init}, \quad (12)$$

$$Q_{b,eap}SOC_b^{\min} \leq E_{b,k} \leq Q_{b,eap}SOC_b^{\max}, \quad k = 0, \dots, N, \quad (13)$$

$$-P_b^{\max} \leq P_{b,k} \leq P_b^{\max}, \quad k = 0, \dots, N - 1, \quad (14)$$

141 where the charge power is assumed to be positive, by convention.

142 3. Optimization problem formulation

143 This section presents the CP approach used for solving the optimal param-
 144 eters design and power management problem for the smart home nanogrid. A
 145 standard CP problem is formulated as

$$\begin{aligned} & \text{minimize} && F(x) \\ & \text{s. t.} && f_i(x) \leq 0, \quad i = 1, \dots, p, \\ & && h_j(x) = 0, \quad j = 1, \dots, q, \\ & && x \in Z \end{aligned} \quad (15)$$

where $Z \in R^n$ is a convex set, $F(x)$ and $f_i(x)$ are convex functions, and $h_j(x)$ are affine functions of optimization vector x . The theoretical and algorithmic aspects of CP are detailed in [38]. The convex objective function $F(x)$, which is of great interest to the home owner, is formulated to minimize a summation of the total electric energy cost in the time horizon of optimization and the home BESS cost, for which we mainly consider the battery cost and charger cost:

$$F = C_{ny} + c_b Q_{b,eap} + c_c P_b^{\max}, \quad (16)$$

where for simplicity, we assume that the total electric energy cost is the same in every year. As a result, we can deduce C_{ny} as follows:

$$C_{ny} = n \sum_{k=0}^{N-1} c_{e,k} P_{grid,k} / 100, \quad (17)$$

It is easy to see that the objective function F is linear, which is convex. The optimization variables include the state variables $E_{ev,k}$ and $E_{b,k}$, the control variables $P_{evc,k}$ and $P_{b,k}$, and the optimal design parameters $Q_{b,cap}$ and P_b^{\max} . The constraints are the home power balance (1), the PEV battery constraints (4)-(10), the home battery constraints (11)-(14), and the grid limits (2). The inequality constraint functions include Eqns (2), (9), (10), (13), and (14), which are linear and thus convex. The equality constraint functions include Eqns (1), (4)-(8), (11), and (12). Obviously, Eqns (1), (5)-(8), and (12) are linear and affine. However, Eqns (4) and (11) are absolute function, which are not affine. In a standard convex optimization problem, only affine equality constraints are tolerated. The total original problem is not a convex problem, due to the absolute equality constraints, which is essentially nonlinear. However, relaxing (4) and (11) to inequalities gives a convex problem without qualitatively altering the original problem as follows:

$$E_{ev,k+1} \leq E_{ev,k} + \Delta t(P_{evc,k} - \eta_{evc}|P_{evc,k}|), \quad k = 0, \dots, N - 1. \quad (18)$$

$$E_{b,k+1} \leq E_{b,k} + \Delta t(P_{b,k} - \eta_b|P_{b,k}|), \quad k = 0, \dots, N - 1. \quad (19)$$

146 Now, Eqn (18) and (19) are absolute inequalities, which are convex, enabling
 147 the problem to become a convex problem. A tool, CVX [38], is employed to
 148 parse the optimization problem, inducing a semi-definite program that can be
 149 efficiently solved by SeDuMi (Self-Dual-Minimization) [39]. It should be under-
 150 lined that thanks to the convexity, a globally optimal solution with arbitrary
 151 initialization can be readily accomplished.

152 4. Results & discussion

153 4.1. System parameters

154 This section analyses the properties of the proposed CP approach. The key
 155 parameters of the smart home are listed in Table 2. All the simulations were
 156 run on a PC with a 2.50 GHz Intel Core i5-2450M CPU and 4 GB of internal
 157 memory. **Thanks to the mentioned advantages of the proposed method, the CP**

158 computational time is less than 30 s using CVX tool in the Matlab environment
159 when optimizing component size and control strategy simultaneously. And the
160 CP computational time is less than 1 s when only optimizing the HEM control
161 strategy with a 24h look-ahead horizon.

162 The hourly home load data and PV power supply data on each day and
163 average from a single family home in California, US [40] are shown in Fig. 2-(a)
164 and (b). The collected data corresponds to date range from 2014-01-01 to 2014-
165 12-31. The hourly home load demand varies from 0.25 kW to 4.58 kW. The
166 peak loads always happen from 7:00-15:00 and 18:00-1:00. The hourly PV power
167 supply varies from 0 to 2.81 kW. It is easily observed that the PV power supply is
168 centralized from 9:00 to 15:00 and sometimes more than the instantaneous home
169 load demand. Referring to Pacific Gas and Electric Company's (PG&E) special
170 EV rate plans for residential customers, they are non-tiered, time-of-use plans
171 as shown in Fig. 2-(c) [41]. The electric price is lowest (10 cents/kWh) from
172 23:00 to 7:00 when the demand is lowest. Electricity is more expensive during
173 Peak (43 cents/kWh, 14:00-21:00) and Partial-Peak (22 cents/kWh, 7:00-14:00
174 and 21:00 to 23:00) periods. Fig. 2-(d) plots the state of the PEV. The PEV
175 plugs-out from 7:00 to 20:00 (not at home) and plugs-in from 20:00 to 7:00 (at
176 home). It is obvious that the house sells electric energy to the grid with Partial-
177 Peak electric price and buys it with peak electric price. If there is a home BESS,
178 users can not only store the redundant PV power, but also buy electric energy
179 with low price for the use of high price time. The home BESS can not only
180 reduce household electric energy costs, but also supply back-up electric energy
181 to the house during lacking of electric power because of blackout.

182 4.2. System parameters optimization

183 Based on the historical home load demand and PV power generation data,
184 as well as the hourly time-varying electric price and state of PEV, the optimal
185 parameters of home BESS and energy management strategy can be procured
186 via CP. In light of the report of Avicenne Energy, the worldwide battery price
187 might vary from 60 \$/kWh to 203 \$/kWh in 2020 [42]. Considering different

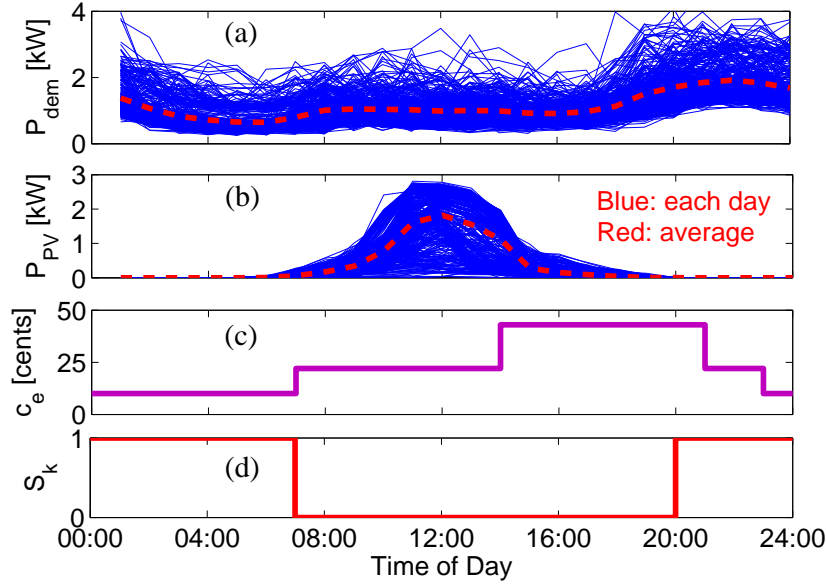


Figure 2: Real-world data of home power demand, PV generation, electric price, and state of vehicle.

188 time horizons of optimization, home BESS prices, different control modes of
 189 PEV, the parameters of home BESS can be explored, as well as the total cost.
 190 First, we consider that the owner has a Nissan Leaf with 24 kWh battery that
 191 cannot discharge power to the home. Independently of the time horizon of
 192 optimization (1 to 10), battery price (60 \$/kWh to 203 \$/kWh), and charger
 193 price (1000 \$/kW) [43], the maximum power P_b^{\max} maintains constant, equals
 194 to 2.26 kW. The reason for this result may be due to the constraint of Eqn
 195 (2), not permitting power supply to the grid. The optimal values of battery
 196 energy capacity $Q_{b, eap}$ are shown in Fig. 3-(a). The battery energy capacity is
 197 augmented as the optimization time horizon increases. The total electric costs
 198 with/without home BESS for different time horizons of optimization are also
 199 shown in Fig. 3-(b).

200 Given the battery price and charger price of 100 \$/kWh and 1000 \$/kW,
 201 as well as different time horizons, the optimal values of home battery energy

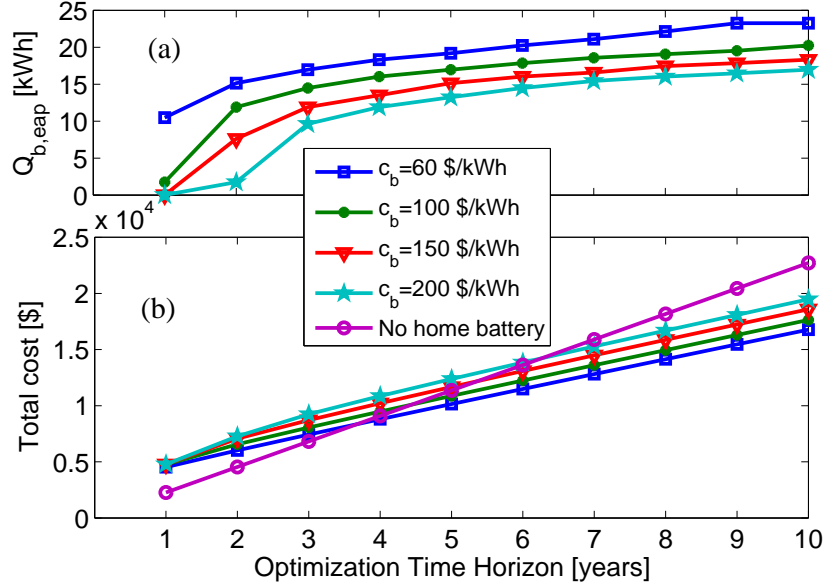


Figure 3: Battery energy capacity and total electric cost, given different time horizons and battery prices.

202 capacity $Q_{b, eap}$, and electric cost are shown in Table 3, where F_e , F , F_{noB} ,
 203 and F_{diff} are the electric cost for one year with home BESS, the total cost
 204 with BESS in n years, the electric cost without BESS, and the cost difference
 205 between the cases with and without BESS in n years, respectively. The home
 206 battery energy capacity increases as the time horizon becomes larger. The total
 207 cost F of the house with home BESS is larger than that in the case of the house
 208 without home BESS, when the time horizon is less than 5 years. However,
 209 when the time horizon is 5 years, the house with home BESS, for instance,
 210 can save 487 \$. The cost savings become more significant with increased time
 211 horizons. If we assume a home battery life to be 5 years [44], the optimal value
 212 of home battery energy capacity that we consider is 17 kWh, and the cost of
 213 home BESS is 3960 \$. With home BESS, the electric energy cost in one year is
 214 1382 \$, whereas without the BESS, the counterpart is 2271.3 \$. The associated
 215 reduction reaches up to around 39.2%.

216 *4.3. Optimal results based on different types and control modes of PEV*

217 This subsection presents the resulting CP control law simulated on smart
218 home with PEVs manufactured by different companies, including Nissan Leaf,
219 Tesla Model S, BYD E6, Chevrolet Volt, and Toyota Prius. Here we assume
220 that the time horizon of optimization is 6 years, and the home battery price
221 and charger price are 100 \$/kWh and 1000 \$/kW. Two control modes of PEV
222 are considered, i.e., H2V and V2H modes. In H2V mode, the PEV battery
223 cannot supply power to the house, $0 \leq P_{evc,k} \leq P_{evc}^{\max}$. In V2H mode, the PEV
224 battery can supply power to the house, $-P_{evc}^{\max} \leq P_{evc,k} \leq P_{evc}^{\max}$ [45].

225 Considering different types of PEVs (with different battery energy capacities
226 and chargers), the optimal parameters of home BESS $Q_{b,eap}$ and $P_{b,max}$, and the
227 total cost are shown in Table 4. In H2V mode and V2H mode, independently
228 of the types of PEVs, the maximum power $P_{b,max}$ keeps constant, equal to 2.26
229 kW. In H2V mode, the optimal value of home battery energy capacity $Q_{b,eap}$
230 is not affected by the EV battery energy capacity. In V2H mode, the optimal
231 values of home battery energy capacity $Q_{b,eap}$ is affected by the EV battery
232 energy capacity, but the influence is very small, i.e., $15.8 \text{ kWh} \leq Q_{b,eap} \leq 16.7$
233 kWh.

234 **With/without** home BESS, the total cost in V2H mode is less than that in
235 H2V mode. For the same type PEV with the same control mode, the total cost
236 with home BESS is less than that without home BESS.

237 *4.4. Example of energy management strategy*

238 This subsection presents the resulting CP control law in a smart home with
239 a Nissan Leaf, simulated on two different operating modes, including H2V mode
240 and V2H mode. The hourly power allocation over two days is described in Fig.
241 4, including the hourly home power demand (P_{dem}), the PV power generation
242 (P_{PV}), the home battery power (P_b), the PEV battery power (P_{evc}), and the
243 electric power from the grid (P_{grid}). In both H2V and V2H modes, it is evident
244 that the majority of the home battery charging occurs during the low electricity
245 price period: 24:00-7:00 and high PV power supply period: 10:00-15:00. Most of

246 the home battery discharging happens during the high electricity price period:
 247 14:00-23:00. The majority of the PEV battery charging occurs during the low
 248 electricity price period: 23:00-7:00. In V2H mode, the PEV discharging power
 249 to the house appears during the high electricity price period and large home
 250 power demand: 21:00-23:00. The electric power from the grid is zero during
 251 the period: 8:00-23:00 in V2H mode. The electric power from the grid is zero
 252 during the period: 8:00-21:00 in H2V mode. In summary, in both H2V and
 253 V2H modes, the home does not buy electric energy from the grid during the
 peak periods of electric price.

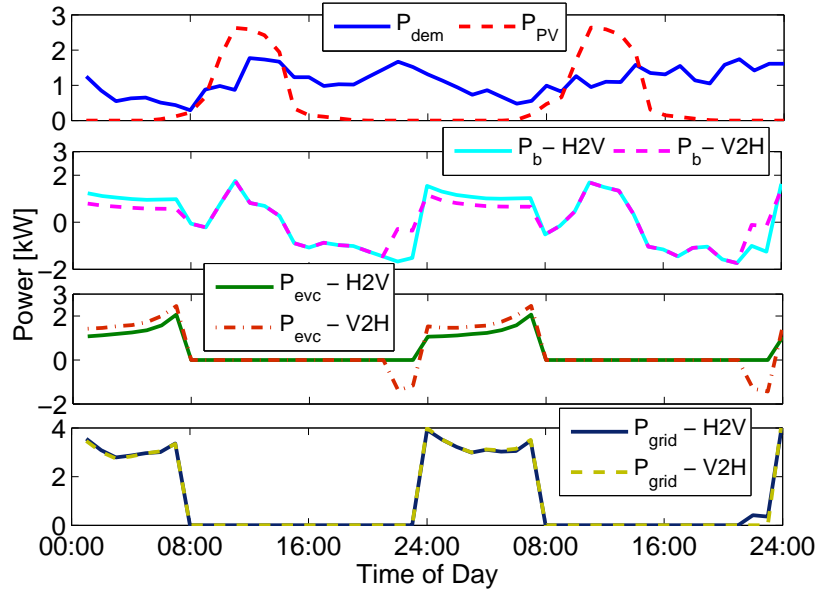


Figure 4: CP-optimized power allocation in two-day simulation.

254
 255 In H2V and V2H modes, energy trajectories of both home and PEV batteries
 256 are illustrated in Fig. 5. The home battery energy in H2V mode is always higher
 257 than that in the V2H mode. When the PEV plugs-in, the PEV battery energy in
 258 H2V mode is higher than that in the V2H mode. In the course of PEV plugging-
 259 out, the PEV battery energy always equal to $SOC_{ev}^{max} Q_{ev, eap}$, because of the
 260 constraints Equ.(6).

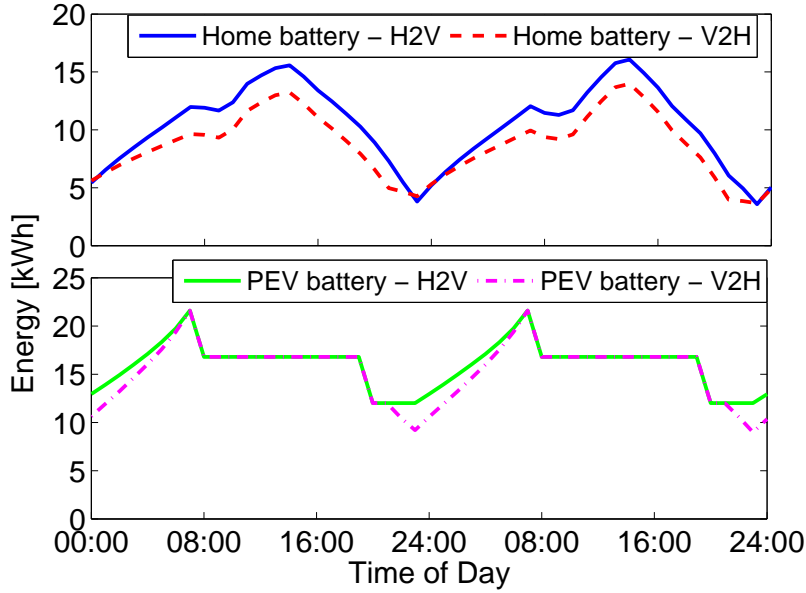


Figure 5: CP-optimized battery energy trajectory in two-day simulation.

261 To demonstrate the potential economic benefits of the smart home nanogrid,
 262 we analyse the electric energy cost in a comparative fashion. The hourly electric
 263 energy cost for two days are shown in Fig. 6, including the cost of home power
 264 demand, the earned money of PV generation, the earned money of home battery,
 265 the cost of PEV battery charging, and the total electric cost. The two-day
 266 electric energy cost of home power demand is 13.90 \$, and the two-day earned
 267 money of PV generation is 6.02 \$. The two-day earned money of home battery
 268 is 4.62 \$ in H2V mode and 4.22 \$ in V2H mode. The two-day cost of PEV
 269 battery charging is 2.13 \$ in H2V mode and 1.59 \$ in V2H mode. The two-day
 270 total electricity cost is 5.39 \$ in H2V mode and 5.25 \$ in V2H mode. Therefore,
 271 the total electric cost in V2H mode is 2.6 % lower than that in H2V mode.

272 5. Conclusions

273 This paper develops a CP framework for optimal energy management and
 274 component sizing of a hybrid solar-battery power source for smart home nanogrid

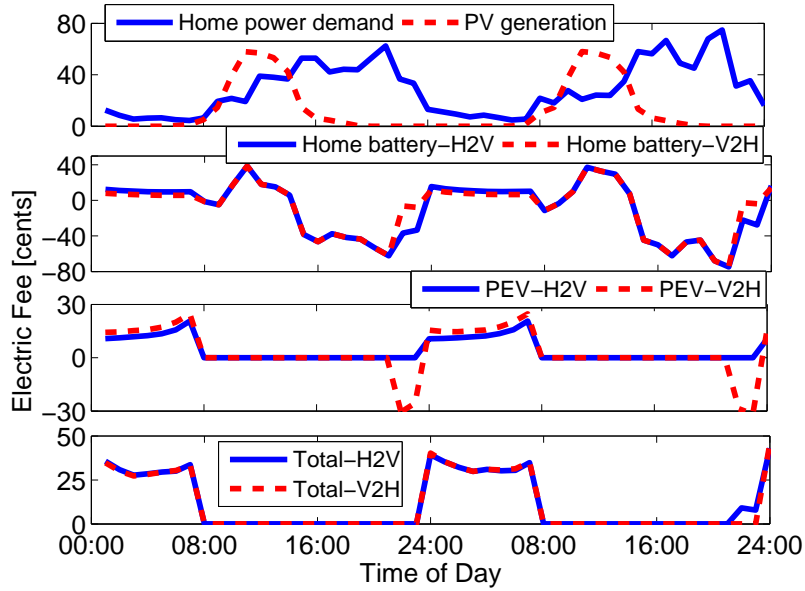


Figure 6: CP-optimized electric energy cost in two-day simulation.

275 with PEV load. The CP problem is mathematically formulated to optimize the
 276 electric power allocation among the PEV battery, home battery, home power
 277 demand, PV arrays, and utility grid. At the same time, the CP strategy explic-
 278 itly takes into account the optimization of home BESS's parameters. Different
 279 time horizons of optimization, home battery prices, types and control modes of
 280 PEVs are also considered in extensive simulation campaigns.

281 Results substantiate that the developed CP method can efficiently solve
 282 the optimization problem, and the home BESS, accounting for a suitable time
 283 horizon of optimization, contributes to significant operational cost savings, in
 284 contrast to the option without home BESS. Further, it is found that the to-
 285 tal electric cost in V2H mode (with bidirectional PEV-to-home/home-to-PEV
 286 power flow) is 2.6 % lower than that in H2V mode (with unidirectional home-
 287 to-PEV power flow).

288 The future work could incorporate more likely uncertainties into the op-
 289 timization framework, regarding the house power demand, time-varying elec-

290 tricity price, renewable power generation, the plug-in/plug-out state of PEV,
291 etc.

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Table 1: Nomenclature

c_b	home battery price per kiloWatt-hour [\$/kWh]
c_c	charger price per kiloWatt [\$/kW]
$c_{e,k}$	electricity price [cents/kWh]
C_{ny}	n -year total electricity cost [\\$]
$E_{ev,k}$	energy of PEV battery [kWh]
$E_{ev,init}$	initial PEV battery energy [kWh]
$E_{ev}^{plug-out}$	energy of PEV battery when the vehicle plugging-out [kWh]
$E_{ev}^{plug-in}$	energy of PEV battery when the vehicle plugging-in [kWh]
E_{dr}	consumed energy for driving in a whole day [kWh]
$E_{b,k}$	energy of home battery [kWh]
$E_{b,init}$	initial home battery energy [kWh]
k	time index
N	final time step of one year
n	time horizon of optimization [year]
$P_{grid,k}$	electric power from the grid [kW]
$P_{dem,k}$	electric load demand of the house [kW]
$P_{b,k}$	electric power of home battery [kW]
$P_{evc,k}$	electric power of PEV battery [kW]
$P_{pv,k}$	power supply of PV arrays [kW]
P_{grid}^{\max}	maximal power from the grid [kW]
P_{evc}^{\min}	PEV battery's minimal power [kW]
P_{evc}^{\max}	PEV battery's maximal power [kW]
P_b^{\max}	home battery's maximal power [kW]
$Q_{evc,eap}$	energy capacity of the PEV battery [kWh]
$Q_{b,eap}$	energy capacity of the home battery [kWh]
S_k	PEV state at time k
t_d	plugging-out time
t_a	plugging-in time
SOC_{ev}^{\min}	PEV battery's minimal SOC
SOC_{ev}^{\max}	PEV battery's maximal SOC
SOC_b^{\min}	home battery's minimal SOC
SOC_b^{\max}	home battery's maximal SOC
Δt	time-step [h]
η_{evc}	lost efficiency of PEV battery
η_b	lost efficiency of home battery

Table 2: Key parameters.

Parameter Description	Symbol	Value	Unit
Step time	Δt	1	hour
Maximum PEV battery SOC	SOC_{ev}^{\max}	0.90	-
Minimum PEV battery SOC	SOC_{ev}^{\min}	0.20	-
Maximum home battery SOC	SOC_b^{\max}	0.90	-
Minimum home battery SOC	SOC_b^{\min}	0.20	-
PEV plugging-out time	t_d	7:00 AM	-
PEV plugging-in time	t_a	8:00 PM	-
Lost efficiency	η_{evc} / η_b	0.10	
Maximum power from grid	P_{grid}^{\max}	10	kW

Table 3: Optimal value ($c_b=100$ \$/kWh and $c_c=1000$ \$/kW).

n/year	$Q_{b,cap}/\text{kWh}$	$F_e/\$$	$F/\$$	$F_{noB}/\$$	$F_{diff}/\$$
1	1.75	2330.9	4765.8	2271.3	2494.5
2	11.90	1554.6	6558.7	4542.7	2016
3	14.49	1448.8	8055.1	6814.0	1241.1
4	16.03	1403.6	9477.2	9085.4	391.8
5	16.97	1382.0	10870	11357	-487
6	17.85	1366.2	12243	13682	-1439
7	18.56	1355.3	13603	15899	-2296
8	19.06	1348.5	14954	18171	-3217
9	19.53	1343.0	16300	20442	-4142
10	20.25	1335.5	17640	22713	-5073

Table 4: Optimal values of home battery energy capacity for different types of PEVs.

	Leaf	Mode S	E6	Volt	Pruis
$Q_{evc,eap}$ (kWh)	24	85	82	16	5.2
P_{evc}^{\max} (kW)	3.6	10	10	3.6	3.6
$Q_{b,eap}$ in H2V mode (kWh)	17.85	17.85	17.85	17.85	17.85
$Q_{b,eap}$ in V2H mode (kWh)	15.9	15.84	15.84	15.98	16.69
$P_{b,\max}$ in H2V mode (kW)	2.26	2.26	2.26	2.26	2.26
$P_{b,\max}$ in V2H mode (kW)	2.26	2.26	2.26	2.26	2.26
Total cost with BESS – H2V (\$)	12243	18188	17896	11463	10410
Total cost with BESS – V2H (\$)	11827	17770	17478	11091	10250
Total cost without BESS – H2V (\$)	13628	19574	19281	12848	11796
Total cost without BESS – V2H (\$)	12919	18843	18550	12193	11517

Optimal integration of a hybrid solar-battery power source into smart home nanogrid with plug-in electric vehicle

Wu, Xiaohua

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