Chapter 11

Energy Management in Microgrids with Plug-in Electric Vehicles, Distributed Energy Resources and Smart Home Appliances

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Abstract Smart Grid is transforming the way energy is being generated and distributed today, leading to the development of environment-friendly, economic and efficient technologies such as plug-in electric vehicles (PEVs), distributed energy resources and smart appliances at homes. Among these technologies, PEVs pose both a risk by increasing the peak load as well as an opportunity for the existing energy management systems by discharging electricity with the help of Vehicle-to-grid (V2G) technology. These complications, together with the PEV battery degradation, compound the challenge in the management of existing energy systems. In this context, microgrids are proposed as an aggregation unit to smartly manage the energy exchange of these different state-of-the-art technologies. In this chapter, we consider a microgrid with a high level of PEV penetration into the transportation system, widespread utilization of smart appliances at homes, distributed energy generation and community-level electricity storage units. We propose a mixed integer linear programming energy management optimization model to schedule the charging and discharging times of PEVs, electricity storage units, and running times of smart appliances. Our findings show that simultaneous charging and discharging of PEV batteries and electricity storage units do not occur in model solutions due to system energy losses.

Keywords Microgrids · Energy management · Optimization · DER · Smart grid · Smart appliances

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11.1 Introduction

The level of information exchange and ease of communication we are witnessing today is transforming the way we interact with the world around us. In the context of energy management, this translates to what has become the “Smart Grid”. This new technology, referred to as “internet of energy” [1], facilitates development of environment-friendly, economic and efficient technologies such as PEVs (plug-in electric vehicles), DERs (distributed energy resources) and smart appliances at homes. Furthermore, classical problems are being reevaluated to cope with these developments. One such problem is the way we manage our daily energy requirements. For decades, electricity generation has always been centralized to reduce the costs and increase the efficiency. Smart Grid is transforming the way energy is being generated and distributed. Today, in addition to reducing costs and increasing efficiency, decentralizing the generation units and making use of renewable, more environmental friendly technologies have become new objectives.

In this context, microgrids are proposed as an aggregation unit to smartly manage the energy exchange of these different state-of-the-art technologies. Microgrid is an electric power system operating in either autonomous mode or connected to an electricity grid. It is formed by DERs, storage units and loads without a large scale infrastructure setup requirement. Due to its independence from the grid, it offers increased reliability. Furthermore, higher efficiencies and increased flexibility can be achieved by microgrids with respect to conventional electricity grids. Due to the smart grid technology, small scale energy resources can efficiently be integrated into the energy management systems. A microgrid generally operates in a confined geography and therefore transmission losses are reduced. Furthermore, it offers reduced costs for its participants.

In this chapter, we consider a microgrid with a high level of PEV penetration into the transportation system, widespread utilization of smart appliances at homes, distributed energy generation and community-level electricity storage units. We propose a mixed integer linear programming (MILP) energy management optimization model to schedule the charging and discharging times of PEVs, electricity storage units, and running times of smart appliances. Furthermore, we show that simultaneous charging and discharging of PEV batteries and electricity storage units do not occur in model solutions due to system energy losses.

11.1.1 Literature Review

The problem of energy management is addressed from several different aspects in the recent literature: Morais et al. [2] search for the least-cost schedule for a number of power resources for the forecast load by using MILP and take into account generators and storage units. Their study is one of the first examples of microgrid energy scheduling. The total cost of generating the energy is minimized and the

forecast load is satisfied. Khodr et al. [3] use the same model with additional power loss constraints and implement it for an experimental setting with in-place power resources. Kriett and Salani [4] consider thermal energy and electricity, and model energy scheduling with the objective of minimizing operating costs. Narahariseti et al. [5] improve the energy scheduling model by adding a constraint to maintain diversity between several resources so that no resource is idle. Moghaddam et al. [6] report a multi-objective model, including pollutant emission minimization and operating cost minimization. They use a variant of the particle swarm optimization (PSO) heuristic to reach a near-optimal solution. Basu et al. [7] author a comprehensive survey about the advantages and disadvantages of the microgrid. The aforementioned microgrid scheduling literature addresses the resource scheduling problem for a forecast load usually with the objective of cost minimization, but does not include PEV battery charging and discharging.

Xiong et al. [8] analyze a home microgrid, comprised of smart appliances capable of responding to hourly changing electricity prices. Pedrasa and Spooner [9] and Rastegar et al. [10] include a PEV as a load in a smart home microgrid. Elma and Selamogullari [11] give another example of the home microgrid scheduling model, but the load is time-inelastic and therefore not schedulable. The home microgrid scheduling literature approaches the energy scheduling problem from the demand side with the perspective of the end-user. It assumes that energy is provided from a single source, determines the on/off status of home appliances to minimize the individual customer cost and regards the PEV as an “appliance” in the house.

Aside from the microgrid energy scheduling literature, several different papers address the energy scheduling problem in PEV-penetrated networks: Fernandes et al. [12] consider massive deployment of EVs (electric vehicles) and investigate the impact of V2G capability on the power system operation in terms of cost, but they do not explicitly provide their models. Studies such as Arslan and Karasan [13] and Sioshansi and Denholm [14] analyze the value of PEVs as grid resources and model the charge scheduling of PEV batteries. Sioshansi and Denholm [14] is a unit commitment model of the Electricity Reliability Council of Texas (ERCOT) electric power system, formulated as an MILP. The objective of the model is to minimize the total system cost, which consists of conventional generator costs and PEV operation costs. The model approaches the problem from the energy generation perspective and neglects the pricing of individual PEV owners. Even though the sum of PEV operation costs is included in the objective function, this does not necessarily imply that the cost for each PEV owner is the least possible cost individually. Arslan and Karasan [13] analyzes the value of PEVs in a virtual power plant (VPP) formation. Several sensitivity analyses are carried out to see the impacts of PEV penetration in different settings. However, smart devices are not considered in [13]. Furthermore, energy trade between the VPP and the national grid is only one sided, that is, the VPP cannot sell its excess energy to the grid. A later study by Sioshansi [15] uses the same model of [14] and includes another aspect to make driving and charging decisions for the PEV owner. As a result, the paper examines the incentives for individual drivers with different electricity tariffs.

Su and Chow [16] propose a PSO algorithm for scheduling PEV charging at a municipal parking station. They model the probabilistic nature of the problem, whose objective function is to maximize the average state of charge for all vehicles in the next time period. Saber and Venayagamoorthy [17] schedule PEV batteries under uncertainty using PSO by taking plug-in and plug-out times with associated probability density functions. Their objective is to minimize the expected cost and emissions. Kristoffersen et al. [18] model EV charging in a market environment from the aggregator's point of view for two cases: when the aggregator is a price-taker and when it has market power. Sousa et al. [19] address the problem of energy scheduling from the microgrid perspective, also considering technical constraints such as bus voltage magnitude and angle limits. In [20, 21], the authors discuss the impacts of PEV specifications, road network features and driver tolerances on the route selection to minimize the costs. In this chapter, we assume that drivers prefer to drive using electricity whenever possible. If not, gasoline is used as the source of energy for transportation.

11.1.2 Problem Definition

We consider a group of house owners coming together to form a microgrid to benefit from economies of scale (Fig. 11.1). Rather than providing the energy solely from the grid, each entity in the new formation is generating a certain level of energy with DERs such as small capacitated photovoltaics and/or wind turbines. Houses have

Fig. 11.1 The microgrid energy management model

time-inelastic (TIE) load demands, e.g. refrigeration or television, which need to be satisfied as soon as demanded. They also have time-elastic (TE) loads and these loads need to be satisfied within a given time frame. TE loads are non-preemptive; once started, the “smart” device must run non-stop for at least a certain amount of time. In addition to TIE and TE loads, the houses also have a number of PEVs with a certain driving profile in a given day. A PEV drives on charge depleting (CD) mode until a certain minimum state-of-charge (SoC) is reached, and switches to charge sustaining (CS) mode preserving the remaining charge in its battery and driving on gasoline. In order to drive on CD mode, PEVs need to be charged when they are connected to the microgrid. The difference between TE loads and PEV charging loads is that the latter can be preemptively charged and does not require continuous energy flow. The PEVs can also supply the energy in their batteries to the microgrid via V2G technology. When charging or discharging PEV batteries, the battery degrades with respect to the level of discharge. Modeling battery degradation is another important aspect of the energy management models. In this respect, PEVs pose both a risk and an opportunity for the existing energy management systems. The microgrid as the energy management unit of the houses is responsible for satisfying the loads that are defined above. The energy generated by the DERs is at the discretion of the microgrid which “smartly” manages the total energy available within the microgrid. If a house is underutilizing DER capacities, the excess generated energy can be used to satisfy another house’s demand. The microgrid also has a number of electricity storage units to balance the network loads and to postpone the usage of generated energy for a short period of time. There is also a trading mechanism between the national grid and the microgrid according to a pricing schema. If the energy generated is in excess of the required load and the storage limits, then the energy can be sold to the national grid. In this context, this work deals with the microgrid energy management model. In Sect. 1.2, we present a mixed integer linear programming model to handle the problem and discuss some insights related to the model. In Sect. 1.3, we provide a realistic case study and discuss the value of the microgrid for its participants. Sensitivity analyses of the results to gasoline prices, electricity prices and driving patterns are carried out in Sect. 1.4.

11.2 Methodology

In this section, we introduce the methodology for energy management of microgrids. First, we define the sets, parameters and variables to be used in the model.

11.2.1 Parameters and Variables

The following sets, parameters and variables are used in the microgrid energy management model. Note that our system of interest is the microgrid. Therefore,

when defining the variables, we used a “+” superscript to indicate that the microgrid is *receiving* the energy, and a “−” superscript to indicate that the microgrid is *providing* the energy.

11.2.1.1 Sets

H	Set of microgrid participant homes
A_h	Set of appliance running tasks (non-preemptive) in home $h \in H$
D_h	Set of DERs in home $h \in H$
P_h	Set of PEVs in home $h \in H$
S	Set of electrical storage units
T	Set of time periods

11.2.1.2 Appliance-Related Parameters

α_{ah}^{app}	Period at which appliance running task $a \in A_h$ at home h can be started
β_{ah}^{app}	Period at which appliance running task $a \in A_h$ at home h must be finished
τ_{ah}^{app}	Non-preemptive running period of appliance task $a \in A_h$ at home h
ψ_{ah}^{app}	Energy requirement of appliance running task $a \in A_h$ at home h in one time period (kWh)

11.2.1.3 PEV-Related Parameters

ϕ_{ph}^{cs}	Gasoline consumption of PEV $p \in P_h$ at home h in CS mode (gallons /mile)
ϵ_{ph}^{cd}	Electricity consumption of PEV $p \in P_h$ at home h in CD mode (kWh/mile)
η_{ph}^{pev+}	Discharging efficiency of PEV $p \in P_h$ at home h
η_{ph}^{pev-}	Charging efficiency of PEV $p \in P_h$ at home h
ρ_{ph}^{pev+}	Total transferable energy from PEV $p \in P_h$ at home h in one period
ρ_{ph}^{pev-}	Total transferable energy to PEV $p \in P_h$ at home h in one period
I_{ph}^{pev}	Initial state of charge for PEV $p \in P_h$ at home h
σ_{ph}^{pev}	1 if PEV $p \in P_h$ at home h is connected to the microgrid for charging/ discharging during period $t \in T$, 0 otherwise
$\bar{K}_{ph}^{pev}$	Maximum capacity of PEV $p \in P_h$ at home h
$\underline{K}_{ph}^{pev}$	Minimum capacity of PEV $p \in P_h$ at home h

d_{pht}^{pev}	Total travel distance during period t by PEV $p \in P_h$ at home h (miles)
c_{ph}^{deg}	Battery degradation cost parameter for PEV $p \in P_h$ at home h (ϕ)

11.2.1.4 DER and Grid-Related Parameters

η_{dh}^{der}	Generation efficiency of DER $d \in D_h$ at home h
c_{dh}^{der}	Cost of energy generation for DER $d \in D_h$ at home h
K_{dht}^{der}	Generation limit of DER $d \in D_h$ at home h during period $t \in T$ (kWh)
c_t^{grid+}	Electricity price of buying from the grid during period $t \in T$ (ϕ)
c_t^{grid-}	Electricity price of selling to the grid during period $t \in T$ (ϕ)

11.2.1.5 Storage Unit-Related Parameters

η_s^{stor+}	Discharging efficiency of storage unit $s \in S$
η_s^{stor-}	Charging efficiency of storage unit $s \in S$
c_s^{stor}	Maintenance cost of storage unit $s \in S$ per period per kWh usage (ϕ)
I_s^{stor}	Initial state of charge for storage unit $s \in S$ (kWh)
ρ_s^{stor+}	Total transferable energy from the storage unit $s \in S$ in one period (kWh)
ρ_s^{stor-}	Total transferable energy to the storage unit $s \in S$ in one period (kWh)
K_s^{stor}	Capacity of storage unit $s \in S$ (kWh)
δ_{st}^{stor}	Battery depth of discharge of storage unit $s \in S$ at the end of period $t \in T$

11.2.1.6 Other Parameters

l_{ht}^{tie}	Time-inelastic load of home $h \in H$ during period $t \in T$ (kWh)
M	Energy trade limit between the grid and the microgrid in one time period (kWh)
c_t^{gas}	Price of gasoline during period $t \in T$ (ϕ)

11.2.1.7 Variables

e_{dht}^{der}	Energy transfer from DER $d \in D_h$ at home h during period $t \in T$ (kWh)
e_t^{grid+}	Energy import from the grid during period $t \in T$ (kWh)

e_t^{grid-}	Energy export to the grid during period $t \in T$ (kWh)
w_t^{grid}	1 if electricity is purchased from the grid during period $t \in T$, 0 otherwise
e_{pht}^{pev+}	Energy transfer from the PEV $p \in P_h$ at home h during period $t \in T$ (kWh)
e_{pht}^{pev-}	Energy transfer to the PEV $p \in P_h$ at home h during period $t \in T$ (kWh)
e_{pht}^{pev}	State of energy of the PEV $p \in P_h$ at home h at the end of period $t \in T \cup \{0\}$ (kWh)
r_{pht}^{pev}	Required energy to run PEV $p \in P_h$ at home h in period $t \in T$ (kWh)
δ_{pht}^{pev}	Battery depth of discharge of PEV $p \in P_h$ at home h at the end of period $t \in T$
b_{pht}^{pev}	1 if PEV $p \in P_h$ at home h is charged during period $t \in T$, 0 otherwise
d_{pht}^{CD}	CD mode travel distance during period $t \in T$ by PEV $p \in P_h$ at home h (miles)
d_{pht}^{CS}	CS mode travel distance during period $t \in T$ by PEV $p \in P_h$ at home h (miles)
e_{st}^{stor+}	Energy transfer from the storage unit s during period $t \in T$ (kWh)
e_{st}^{stor-}	Energy transfer to the storage unit s during period $t \in T$ (kWh)
e_{st}^{stor}	State of energy of the storage unit s at the end of period $t \in T \cup \{0\}$ (kWh)
δ_{st}^{stor}	Battery depth of discharge of storage unit $s \in S$ at the end of period $t \in T$
y_{st}^{stor}	1 if storage unit s is charged during period $t \in T$, 0 otherwise
s_{ah}^{app}	1 if appliance task $a \in A_h$ at home h is started at the beginning of period $t \in T$, 0 otherwise
x_{ah}^{app}	1 if appliance task $a \in A_h$ at home h is running during period $t \in T$, 0 otherwise

11.2.2 Objective Function

The objective of the model is the cost minimization as depicted in Eq. 11.1. The cost is incurred due to energy generation, energy trade with the grid (buying and selling), maintenance of equipment, battery degradations and satisfying transportation requirements.

$$\text{minimize } \sum_{t \in T} \left[c_t^{grid+} \times e_t^{grid+} - c_t^{grid-} \times e_t^{grid-} + \sum_{h \in H} \sum_{d \in D_h} (c_{dh}^{der} \times e_{dht}^{der}) + c_s^{stor} \times \sum_{s \in S} (e_{st}^{stor+} + e_{st}^{stor-}) \right] \\ + \sum_{s \in S} [f(\delta_{st}^{stor}) - f(\delta_{st-1}^{stor})]^+ + \sum_{h \in H} \left(\sum_{p \in P_h} c_t^{gas} \times \varphi_{ph}^{cs} \times d_{pht}^{CS} + c_{ph}^{deg} \times [f(\delta_{pht}^{pev}) - f(\delta_{pht-1}^{pev})]^+ \right) \quad (11.1)$$

The first two terms in the objective function correspond to the price of buying energy from and selling energy to the main grid. If microgrid can satisfy the

demand load by its own resources, then the additional energy generated by the DERs is sold back to grid which is an income. On the other hand, if the resources are not enough for the load at any given period, then the microgrid provides energy from the grid according to a pricing schema set by the grid. The third term in the objective function is for the energy generation cost by the DERs. Even if the resources of some DERs (such as sun or wind) do not incur any cost for the owners, there is a fixed operation and maintenance cost per each kWh of energy generation. Similarly, the fourth term is for the cost incurred due to storage unit maintenance per each kWh of usage. The fifth term corresponds to battery degradation of the storage units. In this term, operator $[\cdot]^+$ equals only a non-negative value. If the term in the parenthesis is less than zero, then the operator returns a zero value. Note that if the battery is charged in period t , then the term in the parenthesis might be a negative value. Thus, we consider the battery cost component when this cost value is non-negative by the $[\cdot]^+$ operator. The battery degradation cost accounts for the battery degradation of the storage units at each charging cycle similar to PEV batteries [13 and 14]. Peterson et al. [22] identifies that in real world applications, the life cycle of a battery is a linear function of the depth of discharge (DoD). Therefore, the degradation cost component in the objective, i.e. function f , is a linear function of DoD difference between periods [13]. The last term is related to the cost incurred by the PEVs. It has the gasoline cost component which is for traveling the distance in CS mode, and the battery degradation cost component similar to storage units degradation.

11.2.3 Energy Balance Constraint

The energy balance between the generation units and the electricity demanding units must be satisfied at every time period. The left hand side of Eq. 11.2 is the summation of the energy that is received by the microgrid. The electricity can be received from the grid, from the storage units, from the PEV batteries by discharging and from the DERs. The right hand side is the summation of the energy that is leaving the microgrid system: the electricity exported to the grid, to the storage units, to the PEV batteries by charging, to the smart appliances at homes and for satisfying the TIE loads.

$$\begin{aligned}
 & e_t^{grid+} + \sum_{s \in S} e_{st}^{stor+} + \sum_{h \in H} \left(\sum_{p \in P_h} \eta_{ph}^{pev+} \times e_{pht}^{pev+} + \sum_{d \in D_h} \eta_{dh}^{der} \times e_{dht}^{der} \right) \\
 & = e_t^{grid-} + \sum_{s \in S} e_{st}^{stor-} + \sum_{h \in H} \left(\sum_{p \in P_h} \eta_{ph}^{pev-} \times e_{pht}^{pev-} + \sum_{a \in A_h} \psi_{ah}^{app} \times x_{aht}^{app} + l_{ht}^{tie} \right) \quad t \in T.
 \end{aligned} \tag{11.2}$$

11.2.4 PEV Modeling

PEV modeling is an important aspect of our formulation and in this section, we model the constraints related to the PEVs. Equation 11.3 sets the upper and lower bounds for the SoC of PEV at every time period. Observe that SoC of a PEV battery is bounded above by the capacity and bounded below by the technical requirements. Typically, a PEV battery is not discharged below 20–30 %.

$$\underline{K}_{ph}^{phev} \leq e_{ph}^{phev} \leq \bar{K}_{ph}^{phev} \quad h \in H, p \in P_h, t \in T \quad (11.3)$$

In Eq. 11.4, we require the energy balance of a PEV battery to hold between periods. The energy at the end of a given period t is equal to the summation of energy at the end of the previous period $t - 1$ and the energy difference in period t . The energy difference might be due to charging or discharging (by the virtue of the V2G technology) when the PEV is connected to the grid, or it might be due to consumption in CD mode transportation. When energy is transferred to PEV, it can only receive a percentage of the transferred energy due to system losses. Similarly, when the energy is transferred from PEV to the microgrid, only a percentage of the energy can be provided to the microgrid. Thus, we make sure that more energy is discharged from the battery to ensure that the required level of energy is provided to the microgrid.

$$e_{ph}^{pev} = e_{ph,t-1}^{pev} + \eta_{ph}^{pev-} \times e_{ph}^{pev-} - \frac{1}{\eta_{ph}^{pev+}} e_{ph}^{pev+} - r_{ph}^{pev} \quad h \in H, p \in P_h, t \in T \quad (11.4)$$

The initial SoC of PEV batteries are set by Eq. 11.5 in which e_{ph0}^{pev} corresponds to the SoC at the beginning of the planning horizon. We also require by Eq. 11.6 that the SoC at the end of the planning horizon is greater than or equal to the same SoC as the beginning state. This makes sure that the PEV is ready for the following day travels.

$$e_{ph0}^{pev} = I_{ph}^{pev} \quad h \in H, p \in P_h \quad (11.5)$$

$$e_{ph,|T|}^{pev} \geq I_{ph}^{pev} \quad h \in H, p \in P_h \quad (11.6)$$

Equations 11.7 and 11.8 make sure that energy cannot be charged to or discharged from PEV batteries if they are not connected to the microgrid. Observe that if the parameter σ_{ph}^{phev} equals to zero, then charge and discharge levels are essentially set equal to zero. If this parameter equals to one, then there is a maximum limit on the charge and discharge levels. Therefore, the same sets of equations also make sure that there is an upper bound on the level of energy that can be charged or discharged in one period. Furthermore, by the use of binary variables, we ensure that the PEV batteries are not simultaneously charged and discharged.

$$e_{pht}^{pev+} \leq \rho_{ph}^{pev+} \times o_{pht}^{pev} \times b_{pht}^{pev} \quad h \in H, p \in P_h, t \in T \quad (11.7)$$

$$e_{pht}^{pev-} \leq \rho_{ph}^{pev-} \times o_{pht}^{pev} \times (1 - b_{pht}^{pev}) \quad h \in H, p \in P_h, t \in T \quad (11.8)$$

The distance to be travelled on CD mode is limited from above by the available energy in the PEV battery. The energy that can be used for transportation is the difference of the current SoC and the minimum SoC level. Dividing this value by the energy consumption of the PEV gives the mileage that can be traveled on CD mode which is ensured by Eq. 11.9.

$$d_{pht}^{CD} \leq \left(\frac{e_{pht-1}^{pev} - K_{ph}^{pev}}{\varepsilon_{ph}^{cd}} \right) \quad h \in H, p \in P_h, t \in T \quad (11.9)$$

Note also that the CD mode trip distance is also bounded above by the total distance that will be traveled in a given time period. This constraint is realized by Eq. 11.10.

$$d_{pht}^{CD} \leq d_{pht}^{pev} \quad h \in H, p \in P_h, t \in T \quad (11.10)$$

If the total travel distance requirement of PEV cannot be traveled solely on CD mode, then the PEV travels the remaining distance on CS mode using gasoline as the source of energy for transportation which is ensured by Eq. 11.11.

$$d_{pht}^{CS} = d_{pht}^{pev} - d_{pht}^{CD} \quad h \in H, p \in P_h, t \in T \quad (11.11)$$

The energy requirement of PEV for transportation is set by Eq. 11.12. The total level of energy that PEV consumes in transportation is the mileage that is actually traveled in CD mode times the energy consumption of PEV per mile.

$$r_{pht}^{pev} = d_{pht}^{CD} \times \varepsilon_{ph}^{cd} \quad h \in H, p \in P_h, t \in T \quad (11.12)$$

DoD is used for obtaining the battery degradation cost in the objective function. Equation 11.13 sets the DoD for each period depending on the current SoC of PEV battery. Observe that it can assume values in [0, 1] range.

$$\delta_{pht}^{pev} = 1 - \frac{e_{pht}^{pev}}{K_{ph}^{pev}} \quad h \in H, p \in P_h, t \in T \quad (11.13)$$

11.2.5 DERs and Grid Modeling

The energy supply is limited by an upper bound depending on the forecast sunshine, wind and/or generation capacity of the DER. The limit is enforced by Eq. 11.14.

$$e_{dht}^{der} \leq K_{dht}^{der} \quad h \in H, d \in D_h, t \in T \quad (11.14)$$

The energy trade between the microgrid and the grid is modeled by Eqs. 11.15 and 11.16. M is the limit of energy transfer. Practically, it can be set to a sufficiently large number. The binary variables in the equations ensure that the energy is not simultaneously transferred both ways in the same time period.

$$e_t^{grid+} \leq M \times w_t^{grid} \quad t \in T \quad (11.15)$$

$$e_t^{grid-} \leq M \times (1 - w_t^{grid}) \quad t \in T \quad (11.16)$$

11.2.6 Electricity Storage Units Modeling

Electricity storage units' modeling has a similar characteristic with the PEV constraints as presented in Sect. 11.2.4. Equation 11.17 models the capacity of the storage unit: the SoC of the storage unit can at most equal capacity.

$$e_{st}^{stor} \leq K_s^{stor} \quad s \in S, t \in T \quad (11.17)$$

Equations 11.18 and 11.19 ensure that charge and discharge is bounded at any given period. Furthermore, simultaneous charging and discharging is avoided by the use of binary variables.

$$e_{st}^{stor+} \leq \rho_s^{stor+} \times y_{st}^{stor} \quad s \in S, t \in T \quad (11.18)$$

$$e_{st}^{stor-} \leq \rho_s^{stor-} \times (1 - y_{st}^{stor}) \quad s \in S, t \in T \quad (11.19)$$

Similar to PEV batteries, the energy of the storage units between periods must be balanced. Equation 11.20 states that the energy level at the end of a given period t is the summation of the energy at the end of the previous period $t - 1$ and the energy change during period t . The energy change is due to charging or discharging. Furthermore, Eq. 11.20 takes into account the system losses. Only a percentage of the energy provided by the microgrid can actually be stored by the unit, and similarly, only a percentage of the energy discharged from the storage unit can actually be used by the microgrid.

$$e_{st}^{stor} = e_{s,t-1}^{stor} + \eta_s^{stor-} \times e_{st}^{stor-} - \frac{1}{\eta_s^{stor+}} \times e_{st}^{stor+} \quad s \in S, t \in T \quad (11.20)$$

Equation 11.21 sets the initial conditions for the storage units and Eq. 11.22 ensures that the SoC at the end of the planning horizon is at least as much as the starting SoC.

$$e_{s0}^{stor} = I_s^{stor} \quad s \in S \quad (11.21)$$

$$e_{s,|T|}^{stor} \geq I_s^{stor} \quad s \in S \quad (11.22)$$

Similar to Eqs. 11.13, and 11.23 sets the DoD for each period depending on the current SoC of storage units.

$$\delta_{st}^{stor} = 1 - \frac{e_{st}^{stor}}{K_s^{stor}} \quad s \in S, t \in T \quad (11.23)$$

11.2.7 Smart Appliances Modeling

The users of smart devices define a feasible time interval for running tasks. Smart devices need to run for a fixed number of periods non-stop. In this regard, Eq. 11.24 models the starting time of the smart devices. Beginning from time period α_{ah}^{app} , the appliance must be started before time period $\beta_{ah}^{app} - \tau_{ah}^{app}$ to be able to finish the task by time period β_{ah}^{app} . Note that $\beta_{ah}^{app} - \tau_{ah}^{app}$ might exceed the planning horizon, i.e. period $|T|$. Thus, we consider the minimum of these two terms when planning the starting time period of the appliance. Once the device is started, Eq. 11.25 ensures that the binary variables indicating that the device is running, $x_{ah,t}^{app}$, is set equal to 1 for the number of periods that the device needs to run. Equation ensures that the variable $x_{ah,t}^{app}$ equals 1 if the appliance is started any time period in the previous τ_{ah}^{app} time periods. Note that the term $t - \tau_{ah} + 1$ might be less than 1. Thus, we only consider the planning horizon, starting from time period 1 until time period T .

$$\sum_{t=\alpha_{ah}}^{\min\{|T|, \beta_{ah} - \tau_{ah}\}} s_{ah,t}^{app} = 1 \quad h \in H, a \in A_h \quad (11.24)$$

$$\sum_{i=\max\{1, t-\tau_{ah}+1\}}^t s_{ahi}^{app} \leq x_{ah,t}^{app} \quad h \in H, a \in A_h, t \in T \quad (11.25)$$

Lastly, Eqs. 11.26 and 11.27 are the domain restrictions of the model.

$$e_{dht}^{der}, e_t^{grid+}, e_t^{grid-}, e_{pht}^{pev+}, e_{pht}^{pev-}, e_{pht}^{pev}, r_{pht}^{pev}, \delta_{pht}^{pev}, e_{st}^{stor+}, e_{st}^{stor-}, e_{st}^{stor}, d_{pht}^{CD}, d_{pht}^{CS} \geq 0$$

$$t \in T, s \in S, h \in H, p \in P_h, d \in D_h, a \in A_h \quad (11.26)$$

$$s_{ah}^{app}, x_{ah}^{app}, b_{pht}^{pev}, y_{st}^{stor}, w_t^{grid} \in \{0, 1\} \quad t \in T, s \in S, h \in H, p \in P_h, a \in A_h \quad (11.27)$$

11.2.8 Binary Variable Reduction

In the above energy management model, we have made use of binary variables in order to model that the results exclude simultaneous occurrence of energy transfer between microgrid and the other entities: PEVs, storage units and the grid. These variables that are traditionally included in the energy management models are actually not required due to system energy losses. To see, we consider two different settings. In the first one, simultaneous charging and discharging of a PEV v occurs in a given time period t . Let c be the energy provided by the microgrid to PEV v , d be the energy received by the microgrid from the PEV v and $e < 1$ be the efficiency of PEV v . In the second setting, the microgrid provides $(c - d)$ units of energy to a PEV v and does not receive any energy from it. Observe that in the second setting, PEV v can only charge $(c \times e)$ units of energy due to system losses, and need to send (d/e) units of energy to the microgrid to make sure that the microgrid receives d units of energy. The net energy stored in the PEV battery is then $(c \times e - d/e)$ units of energy, which is strictly less than $(c - d)$. In both of the scenarios, the net energy difference of the microgrid is the same, but PEV v stores more energy in the second setting. Since the objective function of the above energy management model is cost minimization, the first setting is always a suboptimal solution and the model never simultaneously charges and discharges a PEV in a given time period t .

The same result was also obtained in a different study [13] for a different setting. The same logic also proves that simultaneous charging and discharging of storage units, and simultaneous buying and selling of energy from the national grid is never profitable. Excluding these binary variables from the energy management model ensures speed and efficiency in reaching the optimal solutions.

11.3 Case Study

In this section, we present a case study to observe the model behavior in different settings. The data related to the case study is obtained from official sources as well as recent literature. We consider a group of 100 houses forming a microgrid in California. In addition to TIE loads, the houses have 0, 1 or 2 PEVs, 0, 1 or 2 DERs

and/or 2, 3 or 4 smart devices. The total number of PEVs, DERs and smart appliances in the microgrid are 90, 100 and 300, respectively. The microgrid also has one storage unit. The energy management model above is used for scheduling. 365 days are simulated to observe the impacts in a one-year time period. In the following, we present the data and the experimental design details for the sensitivity analyses.

11.3.1 PEV Data

Four types of PEVs are considered in this study with all-electricity ranges of 7, 20, 40 and 60 miles. The features for each type of PEV are presented in Table 11.1. The capacities of the vehicles, electricity and gasoline consumption data are obtained from [23]. Transferrable energy per period is 7 kWh [24]. The minimum capacity is 30 % of the capacities. The initial SoC is assumed to be the minimum capacity. Cost of gasoline in a day changes between \$4.00 and \$4.10.

The driving data is obtained from the US Department of Transportation's National Household Travel Survey [25]. The number of PEVs travelling in any given period is presented in Fig. 11.2. The peak at 8 a.m. is due to morning commute and a similar peak occurs at close of business hours around 5 p.m.

Travel distances of PEVs are depicted in Fig. 11.3. The average number of travels per vehicle is 2.1 per day in the case study.

11.3.2 DER and Grid Data

We consider three types of DERs that can be used in smart homes: photovoltaics (PVs), wind turbines and natural gas engine with combined heat and power (CHP). The related data is presented in Table 11.2 [26].

Observe that the electricity generation is dependent on two natural factors: sun and wind. Figure 11.4 plots the availability of the sun and the wind as a percentage of its maximum capacity throughout the day [27].

Similarly, these two factors also follow different trends during different seasons of the year [28]. Since we are simulating a year in the case study, we also take into account the seasonal changes of the sun and the wind levels. Figure 11.5 plots the change of wind and sun in a year.

We assume that the grid electricity prices in a given day change in the range of 4.80¢–4.85¢ [29], and that the microgrid sells the excess energy to the grid for half the price that grid sells the electricity for.

Table 11.1 Technical data of the PEV's

PEV type	All electricity range (miles)	Electricity consumption (kWh/mile)	Gasoline consumption (gallons/mile)	Minimum capacity (kWh)	Maximum capacity (kWh)	Charging efficiency (%)	Discharging efficiency (%)
PEV-7	7	0.179	0.0194	0.6	3	90	80
PEV-20	20	0.183	0.02	1.64	8.2	90	80
PEV-40	40	0.188	0.0204	3.36	16.8	90	80
PEV-60	60	0.197	0.0209	5.28	26.4	90	80

Fig. 11.2 Number of PEVs on the road according to the driving patterns

Fig. 11.3 Number of PEV trips for different daily travel distances

Table 11.2 Technical data of the DERs

DER type	Range of capacities (kWh)	Efficiency (%)	Operation and maintenance cost (¢/kWh)	Number in the case study
Photovoltaics	[1, 5]	N/A	0.2	30
Wind turbines	[1, 5]	N/A	1.0	30
Natural gas w/CHP	[1, 5]	85	2.7	30

Fig. 11.4 Energy generation of PVs and wind turbines as percentage of total capacity

Fig. 11.5 Capacity of PVs and wind turbines as percentage of maximum, yearly change

Table 11.3 Technical data of the smart appliances

Appliance type	Energy requirement per period (kWh)	Running hours	Number in the case study
Dishwasher	2.8	2	75
Washer and dryer	2.5	3	75
Water heater	5	4	75
Air conditioner	0.75	5	75

11.3.3 Load and Smart Device Data

The smart appliances in the case study are presented in Table 11.3 [30], and the maximum and minimum limits on the TIE loads are depicted in Fig. 11.6 [31].

Fig. 11.6 Time-inelastic load range per house for a given day

11.3.4 Storage Unit Data

In the case study, we consider a single storage unit with a capacity of 85 kWh and a charging efficiency of 93 % [32]. The cost of battery maintenance per kWh of use is 1¢ [26]. The transfer rate is 19.2 kWh when charging and 14.2 kWh when discharging [33, 34].

11.3.5 Emission Data

In the case study, two types of greenhouse gas (GHG) emissions are considered: NO_x and CO₂. The CHP, grid and gasoline usage are the main sources of GHG emission. The emission for the DERs [26] and PEVs on CS mode [35] is shown in Table 11.4.

11.3.6 Experimental Design

We constructed 365 different datasets with the above baseline data. A total of 100 driving profiles are randomly distributed among PEVs in the scenarios. Every day,

Table 11.4 Emission data of DERs and PEVs (in CS mode)

GHG emission source	NO _x emission	CO ₂ emission
Natural Gas w/CHP (lb/kWh)	0.0059	0.97
National Grid (lb/kWh)	0.005	1.2
PEV7/PEV20 (on CS mode) (g/mile)	0.693	368.4
PEV40/PEV60 (on CS mode) (g/mile)	0.95	513.5

Table 11.5 Scenario settings

Scenario	PEVs	DERs	DER capacities	Gasoline pricing	Electricity pricing	Driving patterns	Smart appliances
1	+	+	Baseline	Baseline	Baseline	Baseline	Baseline
2	–	+	Baseline	Baseline	Baseline	Baseline	Baseline
3	+	–	Baseline	Baseline	Baseline	Baseline	Baseline
4	–	–	Baseline	Baseline	Baseline	Baseline	Baseline
5	+	+	×1.5	Baseline	Baseline	Baseline	Baseline
6	+	+	×2.0	Baseline	Baseline	Baseline	Baseline
7	+	+	Baseline	\$3.50–\$3.60	Baseline	Baseline	Baseline
8	+	+	Baseline	\$3.00–\$3.10	Baseline	Baseline	Baseline
9	+	+	Baseline	\$2.50–\$2.60	Baseline	Baseline	Baseline
10	+	+	Baseline	\$2.00–\$2.10	Baseline	Baseline	Baseline
11	+	+	Baseline	Baseline	9.60¢–9.70¢	Baseline	Baseline
12	+	+	Baseline	Baseline	19.20¢–19.40¢	Baseline	Baseline
13	+	+	Baseline	Baseline	Baseline	×2.0	Baseline
14	+	+	Baseline	Baseline	Baseline	×4.0	Baseline
15	+	+	Baseline	Baseline	Baseline	Baseline	0
16	+	+	Baseline	Baseline	Baseline	Baseline	×2.0

randomly selected smart appliances are required to run. We also randomly assign the TIE loads to the microgrid participant houses. In order to test the impacts of Smart Grid, PEVs, DERs, gasoline and electricity pricing, we built 16 different scenarios as presented in Table 11.5. “Baseline” in the table refers to the data settings presented in Sect. 1.3 above. When the scenario excludes PEVs (i.e. Scenarios 2 and 4), an equivalent performance vehicle is assumed to be in the scenario to travel the required driving patterns.

11.4 Results and Discussion

In this section, we present the results of 16 scenarios, each of which are run for 365 days. For solving the models, IBM ILOG CPLEX Optimization Studio 12.5 was used on a computer with Intel®Core™2 Duo CPU at 2.00 GHz and 2.00 GB RAM. The average solution time for each model is 2.25 s. Daily average energy distribution among generation (grid and DERs) and consumption (PEVs, smart appliances, TIE loads) units are listed in Table 11.6. The corresponding cost and emission values are shown in Table 11.7. In the following part, we shall refer to these tables when discussing the results and providing insights.

Table 11.6 Daily average energy distribution of the microgrid in kWh

Scenario	Grid	DER	PEV	Appliances	TIE loads
1	2926.66	3427.88	395.1	2955.9	2747.7
2	2584.59	3412.44	0.0	2955.9	2747.7
3	6059.13	0.00	395.1	2955.9	2747.7
4	5703.55	0.00	0.0	2955.9	2747.7
5	1360.80	5141.38	395.1	2955.9	2747.7
6	202.84	6388.72	395.1	2955.9	2747.7
7	2926.66	3427.88	395.1	2955.9	2747.7
8	2926.66	3427.88	395.1	2955.9	2747.7
9	2919.24	3427.88	386.8	2955.9	2747.7
10	2584.78	3412.63	0.4	2955.9	2747.7
11	2926.66	3427.88	395.1	2955.9	2747.7
12	2926.66	3427.88	395.1	2955.9	2747.7
13	3198.12	3427.88	696.7	2955.9	2747.7
14	3546.85	3427.88	1084.2	2955.9	2747.7
15	327.13	3020.60	395.1	0.0	2747.7
16	5882.56	3427.88	395.1	5911.8	2747.7

Table 11.7 Daily average cost and emission impacts of the microgrid

Scenario	Cost (¢)	NO _x emission (kg)	CO ₂ emission (kg)
1	30325.48	15.82	3107.68
2	36450.71	15.03	2927.99
3	38370.51	13.75	3304.50
4	44472.55	12.97	3124.25
5	26303.93	16.86	3009.28
6	22989.24	17.57	2927.80
7	30146.85	15.82	3107.68
8	29968.21	15.82	3107.68
9	29789.45	15.81	3104.04
10	27963.66	15.04	2932.15
11	44440.09	15.82	3107.68
12	72669.29	15.82	3107.68
13	42651.78	16.46	3265.40
14	70645.14	17.30	3484.59
15	16691.44	8.84	1513.53
16	44581.47	22.53	4716.61

11.4.1 Value of PEVs and DERs

The base scenario (i.e. Scenario 1) has an average electricity generation of 6,354.6 kWh and consumption of 6,098.7 kWh. The difference between generation and consumption is due to system losses which accounts to 4 % of the generation. When the PEV is excluded from the base scenario, less energy is purchased from the grid. In particular, the amount of reduction is as much as the energy that is used by the PEVs. On the other hand, the cost increases around 20 % when PEVs are excluded. The reason for this effect is that rather than utilizing electricity as the source of energy for transportation, gasoline is used. Thus, the cost increases in Scenario 2. However, counter-intuitively, the emissions are decreasing when more gasoline is used. Observe that the energy that is used by the PEVs to drive on CD mode is solely generated by the grid. The average emissions of the grid (as presented in Sect. 1.3) are higher than that of gasoline. Therefore, we do not observe a reduction in emissions when more electricity is used in transportation. One critical insight is that in order to observe the emission reduction when PEVs penetrate the transportation network, the source of electricity generation for the PEVs will be crucial.

The benefits of DERs can be observed by analyzing the results for Scenarios 1, 3, 4, 5, and 6. Observe that when the DERs are not considered in the microgrid in Scenario 3, the level of electricity to be obtained from the grid is the maximum among the scenarios considered in this study. The cost also increases drastically when compared to the base scenario. When both DERs and PEVs are excluded, i.e. Scenario 4, the cost increase is more than 45 %. When the DER capacities are increased by 1.5 and 2 times in Scenarios 5 and 6, respectively, the cost benefits are between 13 and 25 %. The CO₂ emission also reduces by increasing DER capacities. However NO_x is increasing. This increase is due to the extra NO_x generation by the natural gas with CHP as presented in Table 11.4. Considering a PEV with an average electricity usage of 0.352 kWh per mile, the natural gas with CHP generates 0.96 g of NO_x per mile, the highest amount of emission in our experiments. Therefore, NO_x is increasing in Scenarios 5 and 6. However this increase rests on the assumption that there is no limit on the level of NO_x emission. If the governments put certain limits on the emission levels, then the cost benefits of the microgrid might decrease.

In the base scenario, different PEV types perform differently in terms of electricity utilization in transportation (Fig. 11.7). CD mode usage can be considered as

Fig. 11.7 Travel mode percentage for different vehicle types

the level of advantage that a PEV owner benefits from driving a hybrid vehicle. Thus, the benefits are more for higher all-electricity range vehicles. However, note that the CD more drive percentages almost do not change for PHEV20, PHEV40 and PHEV60. This indicates that after a basic all-electric range is attained (20 miles in our scenarios), the benefits are almost similar for all longer all-electric range vehicles.

11.4.2 Gasoline Pricing Sensitivity

Scenarios 7–10 are dedicated to analyzing the results' sensitivity for gasoline prices. Observe that decreasing the costs does not affect the PEV electricity requirement to a great extent in Scenarios 7, 8, and 9 (Table 11.6). However, in Scenario 10, the energy requirement for PEVs is practically zero. This indicates that there is a critical gasoline pricing between \$2.0 and \$2.5 beyond which drivers prefer gasoline over electricity drive. This is another critical insight of this study.

11.4.3 Electricity Pricing Sensitivity

In scenarios 11 and 12, we consider electricity pricing by the national grid twice and four times more than the baseline pricing, respectively. Even though costs are increased in both scenarios, the electricity purchase from the grid has not changed. The reason is that DERs are utilized at full capacity in even the baseline scenario so that increasing the prices does not significantly affect the amount of electricity purchase. The microgrid still needs to satisfy the loads. Therefore the microgrid purchases the energy that it requires in excess of the generation capacity of the DERs from the grid regardless of the price.

11.4.4 Driving Patterns

Increasing the driving mileage by two and four times in Scenarios 13 and 14, we observe a gradual increase in the cost and the electricity purchase from the grid. Note that the impact of traveling longer distances is significant and might result in doubling the total costs, however impact on emissions is not that significant.

11.4.5 Smart Appliances

In the last two scenarios, we consider excluding the smart devices from the scenarios and doubling the number of devices. Both of the scenarios give the same effect: the cost is halved or doubled as expected. The reason is the change in the amount of electricity purchase from the grid.

11.5 Conclusions

In this study, we consider a microgrid that manages the DERs, PEVs, and smart devices with the objective of cost minimization. The opportunities of microgrids over classical national grid are investigated. Smart management of loads is a way to tackle the excess energy requirement of PEVs as well as peak load increase. High level of PEV penetration into the transportation system, widespread utilization of smart appliances at homes, distributed energy generation and community-level electricity storage units all complicate the energy management problem, however if smartly managed, these complications can be regarded as strengths and opportunities for the next generation energy management units: the microgrids.

In this scope, we propose a mixed integer linear programming energy management optimization model to schedule the charging and discharging times of PEVs, electricity storage units, and running times of smart appliances. Our findings show that simultaneous charging and discharging of PEV batteries and electricity storage units do not occur in model solutions due to system energy losses.

Critical insights are also presented in this study. First of all, in order to observe the emission reduction when PEVs penetrate the transportation network, the source of electricity generation for the PEVs is crucial. If charged from renewable, more benefits can be attained. However charging from the national grid reduces the benefits of PEVs and might even increase the emission level. Another important result is that after a basic all-electric range, cost and emission benefits are almost similar for all longer all-electric range vehicles. This range is 20 miles in this study. Lastly, there is a critical gasoline pricing between \$2.0 and \$2.5 beyond which drivers prefer gasoline over electricity drive.

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