Efficient use of Renewable Energy with Storage and E-Mobility Service

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Abstract

We consider a stochastic and dynamic decision problem of an innovative private household acting as a "prosumer" in the energy market. The household is equipped with a renewable energy source, with a stationary energy storage device and with an electric vehicle. Its goal is maximization of profits from both trading energy and offering a car sharing service to customers. We formulate the problem as a Markov Decision Process and propose two policies for solving the problem. The policies are evaluated in terms of their performance.

Keywords: Energy and Mobility Services, Energy Storage, Plug-In Electric Vehicles, Stochastic Optimization

1. Introduction

The recent technological progress in the areas of energy storage (Blonbou, 2013) and electric vehicles (Manzetti and Mariasiu, 2015) enables new ways of utilizing renewable energy. Hence, both companies and private households that generate renewable energy do face new opportunities of turning this energy into profits. To ensure high profits, operators of renewable energy generating units need to constantly make the right decisions about energy use. In many cases, however, making economically efficient decisions about the use of currently generated renewable energy is a major challenge. Algorithmic decision support is needed in order to address this challenge.

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In this work, we propose and compare two approaches to algorithmic decision support for an innovative private household with a source of renewable energy, battery storage and a plug-in electric vehicle. The household acts as a "prosumer", i.e., energy market access is granted and the generated energy may be used to satisfy the household's own demand. Moreover, the household provides a mobility service in terms of sharing its electric vehicle. If the vehicle is available at the charging station it may be rented by a customer for a per distance fee. As the households goal is to operate its energy system with maximum profit, and as each of generated amount of energy, load, energy market price and transportation demand is subject to stochastic variations over time, the system operator needs to repeatedly adapt its decisions about energy flows. At each point in time, decisions are made about how much energy to transfer between renewable source, storage device, vehicle battery and electricity grid while satisfying the household's energy demand.

Within the past few years an increasing discussion about innovative business models with electric vehicles can be observed (e.g. Budde Christensen et al., 2012). In this context electric vehicle sharing has been identified as one of the service-oriented new business models (see, e.g. Kley et al., 2011) that may involve sharing personal electric vehicles on a peer-to-peer basis (Lue et al., 2012). Weiller and Neely (2014) present a study of the various energy services that electric vehicles can provide and conclude that residential applications such as vehicle-to-home and smart home systems are realizable in the near future. Moreover, Geelen et al. (2013) stress the need for better service design that supports private households in their role as prosumers in a smart grid. Tan et al. (2016) review approaches to integration of electric vehicles into smart grids and propose the use of bidirectional vehicle to grid technology in order to optimize the efficiency of renewable energy sources. Concerning the combination of renewable energy and electric vehicle a number of studies illustrate that renewables could (Bellekom et al., 2012; Hennings et al., 2013) and should (Ajanovic and Haas, 2015) be the only source of energy for electric vehicles. For a recent review on electric vehicles interacting with renewable energy in smart grid we refer to Liu et al. (2015).

Our work connects the area of electric vehicle services with the area of energy storage optimization in the presence of renewable energy. We refer to Powell and Meisel (2015b) for a recent overview of optimization approaches to energy storage problems, and to Banos et al. (2011) for an overview of optimization in the presence of renewable energy.

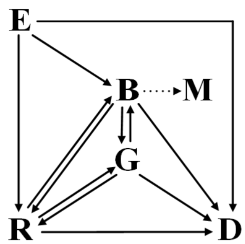


Figure 1: Solid line arrows represent energy flows in kWh between energy source (E), stationary storage (R), car battery (B), grid (G), household's demand (D) and customer demand (M).

2. Problem Formulation

We rely on the canonical modeling framework proposed by Powell and Meisel (2015a) for representing the decision maker's problem as a Markov Decision Process. New decisions about energy flows are made at discrete points in time $t \in \{0, ...T\}$ over a given time horizon of, e.g., one week.

2.1. State Variable and Decision Space

At time t the decision maker observes the energy system's current state

$$S_t = (D_t, M_t, P_t, E_t, R_t, B_t, A_t, f_t),$$

where D_t represents the household's current demand for energy, P_t is the current retail electricity price, E_t is the currently generated renewable energy, R_t is the current amount of energy in the stationary storage device, B_t is the current amount of energy in the electric vehicle's battery and M_t is the current customer demand for transportation in km. We assume that customers book the vehicle for a predefined number of time steps and that A_t always indicates the number of time steps remaining until the vehicle returns, i.e., $A_t = 0$ indicates that the vehicle is on-site. Moreover, we assume that we have access to forecasts of $D_{t'}$, $M_{t'}$, $P_{t'}$ and $E_{t'}$ for all $t' > t$, and that these forecasts are represented as four vectors $f_t = (f_t^D, f_t^M, f_t^P, f_t^E)$.

With capital letters in the superscripts denoting origins and destination of flows, as given in Figure 1, the decisions at time t may be represented as

$$x_t = (x_t^{ED}, x_t^{RD}, x_t^{BD}, x_t^{GD}, x_t^{ER}, x_t^{BR}, x_t^{GR}, x_t^{RG}, x_t^{BG}, x_t^{EB}, x_t^{RB}, x_t^{GB}, x_t^m),$$

where x_t^m is a binary variable indicating whether or not a customer takes the electric vehicle. Note that we assume that the decision maker always shares his car if possible, i.e., if the car is on-site and if the current battery charge level is sufficient. With these assumptions the set of feasible decisions at time t is defined by Equations 1–21:

$$x_t^{ED} + \eta_R^d x_t^{RD} + \eta_B^d x_t^{BD} + x_t^{GD} = D_t + E_t^- \quad (1)$$
$$\eta_R^c(x_t^{ER} + \eta_B^d x_t^{BR} + x_t^{GR}) \leq R^C - R_t \quad (2)$$
$$\eta_B^c(x_t^{EB} + \eta_R^d x_t^{RB} + x_t^{GB}) \leq B^C - B_t \quad (3)$$
$$x_t^{RD} + x_t^{RB} + x_t^{RG} \leq R_t \quad (4)$$
$$x_t^{BD} + x_t^{BR} + x_t^{BG} \leq B_t \quad (5)$$
$$x_t^{ED} + x_t^{ER} + x_t^{EB} \leq E_t^+ \quad (6)$$
$$x_t^{ER} + x_t^{GR} + \eta_B^d x_t^{BR} \leq \delta_R^c \quad (7)$$
$$x_t^{RD} + x_t^{RB} + x_t^{RG} \leq \delta_R^d \quad (8)$$
$$x_t^{EB} + x_t^{GB} + \eta_R^d x_t^{RB} \leq \delta_B^c \quad (9)$$
$$x_t^{BD} + x_t^{BR} + x_t^{BG} \leq \delta_B^d \quad (10)$$
$$A_t \leq K(1 - y_t) \quad (11)$$
$$1 - A_t \leq K y_t \quad (12)$$
$$M_t' - B_t \leq K(1 - z_t) \quad (13)$$
$$M_t' - B_t > -K z_t \quad (14)$$
$$x_t^m \leq z_t \quad (15)$$
$$x_t^m \leq y_t \quad (16)$$
$$M_t' > -K(1 - x_t^m) \quad (17)$$
$$y_t, z_t, x_t^m \in \{0, 1\} \quad (18)$$
$$x_t^{BD} + x_t^{BR} + x_t^{BG} + x_t^{EB} + x_t^{GB} + x_t^{RB} \leq K(1 - x_t^m) \quad (19)$$
$$x_t^{BD} + x_t^{BR} + x_t^{BG} + x_t^{EB} + x_t^{GB} + x_t^{RB} \leq K y_t \quad (20)$$
$$x_t^{ED}, x_t^{RD}, x_t^{BD}, x_t^{GD}, x_t^{ER}, x_t^{BR}, x_t^{GR}, x_t^{RG}, x_t^{BG}, x_t^{EB}, x_t^{RB}, x_t^{GB} \geq 0 \quad (21)$$

We consider the fact that a generating unit such as a wind turbine consumes energy during operations by letting $E_t^- = -1 \cdot \min(0, E_t)$ and $E_t^+ = \max(0, E_t)$. The (dis-)charge efficiencies of stationary storage and vehicle battery are denoted as η_R^d, η_R^c, η_B^d and η_B^c. Accordingly, we denote the storage device's (dis-)charge rates as δ. R^C and B^C are the storage capacities. M_t' denotes the transportation demand converted into kWh and K is a very large number.

2.2. State Transition and Objective Function

The transition from state S_t to successor state S_{t+1} is determined by both decisions x_t and uncontrolled exogenous influences W_{t+1}. We model these influences as changes $W_t = (\hat{D}_t, \hat{M}_t, \hat{P}_t, \hat{E}_t, \hat{f}_t)$ of D_t, M_t, P_t, E_t and f_t.

The profit at a point in time results as the sum of (a) money made by selling energy to the market, (b) money gained from car sharing, (c) opportunity costs of satisfying the household's demand from renewables, minus (d) the money spent on buying energy. The total profit at time t is defined as

$$C(S_t, x_t) = P_t(D_t + \eta_R^d x_t^{RG} + \eta_B^d x_t^{BG} - x_t^{GR} - x_t^{GB} - x_t^{GD}) + \alpha M_t x_t^m,$$

where α is the fee we charge the car sharing customers per km. The decision maker aims at finding an optimal policy, i.e., an optimal decision rule, $X_t^\pi(S_t)$, that given any system state S_t returns the best feasible decisions. His overall goal is the maximization of the expected sum of profits over the entire time horizon, which results into the objective function

$$\max_{\pi \in \Pi} \mathbb{E}^{\pi} \sum_{t=0 \ldots T} C(S_t, X_t^{\pi}(S_t)). \tag{22}$$

3. Policies

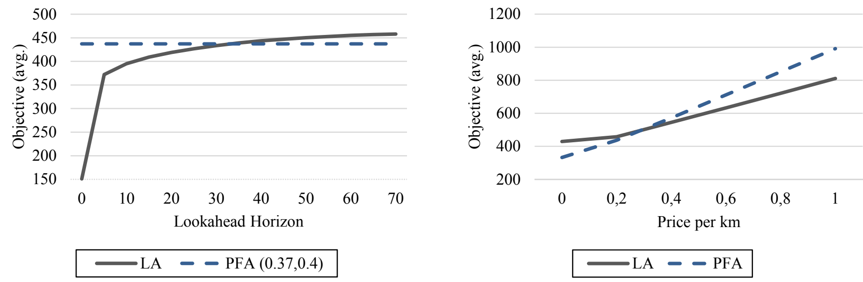
Due to the well-known curses of dimensionality (see, e.g., Powell, 2011) problem (22) typically turns out to be computationally intractable for real-world applications. As an optimal policy cannot be computed, we propose and compare the performances of two alternative policies.

Policy Function Approximation (PFA). PFAs are analytic functions that map states to decisions without solving an optimization problem. We propose a PFA, $X_t^{PFA}(S_t|\theta^L, \theta^U)$, with tunable parameters θ^L and θ^U. The PFA is in the spirit of the PFA proposed by Powell and Meisel (2015b) for an energy storage problem. For the sake of brevity, we do not provide a formal definition of the PFA, but describe its logic at each point in time t. As much of E_t as possible is used for satisfaction of the household's demand. Then, as much of the remaining energy as possible is transferred to the stationary storage. As much as possible of the still remaining energy is then transferred to the car battery. If part of the demand is still unsatisfied and if $P_t \le \theta^L$, we buy energy at the market in order to satisfy the remaining demand. If $P_t > \theta^L$, we first rely on the stationary storage as much as possible, before we rely on the car battery as much as possible and buy any additional energy needed for demand satisfaction at the market. If $P_t > \theta^U$, as much energy from the two storages as possible is sold to the market, and if $P_t \le \theta^L$, as much energy as possible is bought at the market and stored in the two batteries.

Lookahead (LA) Policy. We propose a deterministic LA policy $X_t^{LA}(S_t|\theta^H)$, with the lookahead horizon as the tunable parameter θ^H. The LA policy determines the decisions x_t by solving the optimization problem

$$\arg\max_{\tilde{x}_t} \sum_{t'=t}^{t+\theta^H} f_{tt}^P (f_{tt}^D + \eta_R^d \tilde{x}_{tt'}^{RG} + \eta_B^d \tilde{x}_{tt'}^{BG} - (\tilde{x}_{tt'}^{GR} + \tilde{x}_{tt'}^{GB} + \tilde{x}_{tt'}^{GD})) + \alpha \cdot f_{tt}^M \cdot \tilde{x}_{tt'}^m,$$

where the set of feasible decisions is defined along the lines of constraints 1–21 for each t' with $t \le t' < t + min(T-t, \theta^H)$, and where the decision vectors for points in time $t \ldots t + min(T-t, \theta^H)$ are represented by $\tilde{x}_t = (\tilde{x}_{tt}, \tilde{x}_{t,t+1}, ..., \tilde{x}_{t,t+min(T-t,\theta^H)})$. For notational convenience we define $f_{tt}^D = D_t$, $f_{tt}^M = M_t$, $f_{tt}^E = E_t$ and $f_{tt}^P = P_t$.



(a) Weekly profits with $\alpha = 0.2$. (b) Weekly profits with $\theta^H = 70$.

Figure 2: Comparison of weekly profits.

4. Computational Results

In this section, we showcase one illustrative example of the policies' performances. The considered problem instance is derived from Problem 2 in Meisel and Powell (2016). We adopted the characteristics of all stochastic processes, but scaled them to the numbers that correspond to an average household in Germany. The capacity of the stationary storage is $R^C = 10$ kWh with $\delta_R = 3.3$ kW and $\eta_R = 0.9$. The simulated time horizon is one week and one time interval is set to 15 minutes. The electric vehicle has battery capacity $B^C = 85$ kWh with $\delta_B = 10$ kW, $\eta_B = 0.85$ and a consumption rate of 20 kWh per 100 km. The stochastic demand for transportation varies between 0 and 100 km. We estimate the quality of a policy by generating $n = 100$ sample paths for the exogenous processes and by approximating $\mathbb{E}^\pi \sum_{t=0...T} C(S_t, X_t^\pi(S_t))$ by sample average.

Figure 2a compares the performances of PFA (with manually tuned parameters) and LA policy (with different lookahead horizons) at a per km fee of $\alpha = 0.2$ €, which is about the average fee in German car sharing services. The figure allows for the conclusion that the LA policy should be preferred over the PFA provided that $\theta^H > 33$. However, Figure 2b shows that the advantage of the LA policy critically depends on α. As soon as $\alpha > 0.3$ the tuned PFA clearly outperforms the LA policy.

5. Conclusions

We present a model of a dynamic decision problem of an innovative household that acts as a "prosumer" in the energy market and that provides customers with a e-vehicle sharing service. For solving the problem we propose and compare a lookahead policy and a policy function approximation. Our computational results show that the preferred policy depends on the service fee.

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