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A linear programming approach to the optimization of residential energy systems

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ABSTRACT

A decision-support tool (ORES) in the form of a linear program is developed to determine the optimal investment and operating decisions for residential energy systems. It shows how energy conversion units such as a cogeneration fuel cell, a heat pump, a boiler, photovoltaic panels and solar thermal collectors can be combined with energy storage devices, consisting of a battery and a hot water tank, to drive down total yearly energy costs and CO_2 emissions while meeting space heat, hot water and electricity needs. Under the assumption of perfect demand and production forecasts and depending on how the dwelling is allowed to exchange electricity with the grid, cost reductions between 5 and 60% are possible, whereas emissions can be cut by 45–90% with respect to a base case. Stochastic programming is used effectively to reduce the sensitivity to uncertainty in weather parameters. The resulting cost increase is limited to 1.2%. Decision rules are implemented to account for unforeseen variations in electric load. If it is assumed that peak loads can occur at any instant of the optimization horizon, energy costs rise by 9%, which in off-grid scenarios, are driven by the installation of an about 50% bigger battery system.

1. Introduction

Does it make economic or environmental sense today to power homes with locally converted energy? According to the Swiss Federal Office of Energy [1] residential demand is responsible for one third of the final energy consumption in Switzerland. In the European Union, the residential sector has – at 27% [2] – a slightly smaller share of the final consumption. Households use three types of energy: space heat, domestic hot water and electricity. It is noteworthy, that the heating load is about five times bigger than the hot water and the electric load. This article addresses the role of local conversion by proposing a flexible optimization set-up that considers the economic and technical parameters of decentralized energy conversion and storage systems, as well as the cost and carbon intensity of using grid electricity and natural gas.

There are many ways to provide for the energy needs of a building. One of the more innovative ones is to use a cogeneration fuel cell to produce both heat and electricity. With the increasing penetration of intermittent energy sources such as wind and solar, storage becomes more important to balance energy demand and supply – especially when exchanges with the electrical grid are limited. The present work models five residential energy conversion systems: a cogeneration fuel cell, a natural gas boiler, a heat pump, photovoltaic (PV) panels and solar thermal collectors. Furthermore, a battery and a heat tank are considered for energy storage. The question at hand is how to size and operate these systems in order to minimize annualized energy costs or CO_2 emissions or both. If storage was disregarded and if each unit could produce only either heat or electricity, the screening curve method as described for example by Buehring et al. [3] or more recently by Stoft [4] can give insights on the most economic investment. Since these conditions are not given in this case, linear programming is used to determine the investment and control decisions for a given set of weather, energy consumption and cost data. The advantage of linear programming is that it guarantees the most economic or least emission solution. It does however require a linear model of all conversion and storage units. The relative importance of minimizing CO_2 emissions over energy costs is set by attributing a cost to each ton of CO_2 emitted to the atmosphere. There are four stakeholders who may profit from the proposed tool:

1. households are informed about which energy system would best suit their needs,

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2. policy-makers can test the impact of subsidy schemes, such as feed-in-tariffs or net-metering, and steering taxes (e.g. a tax on CO_2 as it already exists in industry),
3. companies gain information about how to size their products to make them the most attractive to the residential market and
4. researchers can study how a new technology can be integrated into the residential energy mix.

Several scholars have worked on choosing the optimal set of energy conversion and storage units for buildings. Araz Ashouri has written his doctoral thesis on the simultaneous optimal design and control of energy systems on a building level [5]. He used a typical meteorological year (TMY) as input data for the outside temperature and the solar irradiation. His thesis does include combined heat and power systems, but he does not explicitly consider fuel cells. Ashouri's work is focused on applications to commercial and large office buildings, which due to their size tend to have a less fluctuating consumption than residential dwellings. The resulting optimization problem has a horizon of one year with hourly resolution. The choice of the time step is essential since it determines the demand and supply fluctuations that are covered by the optimization problem. Wright and Firth [6] have pointed out that averaging electric load data over 1 h periods significantly underestimates the load variability. The same is likely to hold true for hot water consumption and PV production, whereas space heat requirements may be less variable due to the thermal mass of the building. For the sake of computational tractability, this article follows Ashouri and the microgrid optimization packages presented below in choosing an hourly time step.

The U.S. Department of Energy (DOE) has been involved in the development of two software packages for the design of hybrid energy systems. The Lawrence Berkeley National Laboratory (LBNL) in cooperation with the California Energy Commission began to work on the Distributed Energy Resources Customer Adoption (DER-CAM) Model in 2000 [7]. The tool has been used mostly for the design of rather large microgrids [8–10]. Indeed, the smallest fuel cell that can be considered in the web based version of DER-CAM is 100 kW_{el} – about 40 times bigger than common peak loads in residential systems.

The microgrid modeling company HOMER Energy LLC was founded in 2009 with the goal of commercializing the Hybrid Optimization of Multiple Energy Resources Model (HOMER) developed at the National Renewable Energy Laboratory (NREL), a division of the U.S. DOE [11]. HOMER models a variety of energy technologies; among others, it includes a photovoltaic, a fuel cell, a boiler, and a battery system. It does not model a heat pump, a heat storage and solar thermal collectors. The program has been repeatedly used for the design of residential energy systems [12–15]. In these works, the focus usually lies on covering electric load. This is admissible, if it is presupposed that hot water and space heat loads are covered by either direct electric heating or by a heat pump, since it is ultimately electricity that provides the necessary heat. In this study, the choice of which technologies are responsible for covering heat loads is up to the optimization problem and not taken a priori. Another main difference is that the tool developed here, the Optimization of Residential Energy Systems (ORES), is based on linear programming, meaning that it solves an optimization problem specified by a cost function and a set of constraints, whereas HOMER uses decision rules to explore user-specified design points for the sizes of the energy systems to be installed. While this work was under review HOMER released a derivative free optimization approach inspired by genetic algorithms that mostly eliminates the need to specify discrete design points. It is a non-deterministic approach meaning that HOMER is not guaranteed to find the optimal investment and dispatch decisions. However, due to its simulation based nature, HOMER can capture non-linearities in the energy system. Furthermore, since the HOMER dispatch is governed by decision rules based on experience, it may be more robust towards uncertain demand and supply forecasts than the deterministic version of ORES. Under two admittedly strong assumptions, ORES is guaranteed to find the optimal investment and dispatch decisions. The first is that all cost and conversion parameters are independent from the investment and control decisions. This is a prerequisite for the model to be linear. The second assumption is that all parameters are known deterministically for the entire planning horizon, i.e. for one year, with hourly resolution.

Sections 2 and 3 explain how the household energy systems are modeled. Subsequently, the performance of ORES is benchmarked against HOMER. A comparison between the ORES designed system with a conventional system consisting of a gas boiler for heat and access to the electrical grid will show that – for the Swiss case – the integration of alternative energies can reduce both yearly energy costs and carbon emissions. An analysis of 12 years of meteorological data for the town Ecublens, Switzerland, shows that stochastic programming can be used efficiently to render the program more robust towards changes in weather parameters. Finally, the impact of mitigating load uncertainty through decision rules is investigated.

2. Methodology

The energy flow diagram (Fig. 1) shows from left to right the energy sources, conversion units, storage units and the energy utilization that may be part of a residential energy system. The aim of the optimization problem is to route energy from left to right, i.e. from source to utilization, with the lowest cost. It is possible to optimize only a subset of conversion and storage units such as for example a PV system, a fuel cell and a battery.

For each time-step $t \in T$, where T is the horizon of the optimization problem, each conversion unit relates at least one element s of the set of energy sources

$$S = \{\text{Solar}(sun), \text{Electricity}(el), \text{Gas}(gas)\}$$

to at least one element u of the set of energy services.

$$U = \{\text{Space Heat(sph)}, \text{Domestic Hot Water(dhw)}, \text{Electricity(el)}\}$$

Each conversion unit is described by three parameters (all in W): the installed capacity x, the inflowing power $x^+_{s,t}$ and the outflowing power $x^-_{u,t}$ at each time-step. Similarly, storage units are described by the installed capacity y in J, the inflowing power $y^+_{u,t}$ and the outflowing power $y^-_{u,t}$. The power flowing out of a storage unit must be of the same type as the power flowing into a storage unit. The optimization problem based on the energy flow diagram takes the form:

$$\underset{x,x^+,x^-,y,y^+,y^-}{\text{minimize}} \quad \boldsymbol{c}_x^{\mathrm{T}}\boldsymbol{x} + \boldsymbol{c}_y^{\mathrm{T}}\boldsymbol{y} + \Delta t \sum_t \boldsymbol{c}_{op}\boldsymbol{x}^+{}_t \tag{2.1a}$$

$$\text{subject to} \quad {}_{\boldsymbol{K}}\boldsymbol{x} \leq \boldsymbol{x}_t^+ \leq \boldsymbol{K}\boldsymbol{x} \qquad \forall t \tag{2.1b}$$

$$\boldsymbol{0} \leq \boldsymbol{H}^-\boldsymbol{x}_t^- \leq \boldsymbol{H}^+\boldsymbol{x}_t^+ \qquad \forall t \tag{2.1c}$$

$$\boldsymbol{A}\boldsymbol{x}_t^- - \boldsymbol{B}\boldsymbol{y}_t^{\pm} = \boldsymbol{L}_t \qquad \forall t \tag{2.1d}$$

$$\boldsymbol{0} \leq \boldsymbol{y}_t^+ \leq \boldsymbol{P}^+\boldsymbol{y} \qquad \forall t \tag{2.1e}$$

$$\boldsymbol{0} \leq \boldsymbol{y}_t^- \leq \boldsymbol{P}^-\boldsymbol{y} \qquad \forall t \tag{2.1f}$$

$$\boldsymbol{M}_0\boldsymbol{y} \leq \Big(\sum_{\tau=1}^{t} \boldsymbol{E}^{t-\tau}(\boldsymbol{H}^+\boldsymbol{y}_\tau^+ - \boldsymbol{H}^-\boldsymbol{y}_\tau^-) - (\boldsymbol{M}_1 + \boldsymbol{M}_2\boldsymbol{y})\Big)\Delta t + \boldsymbol{E}^t\boldsymbol{y}_0 \leq \boldsymbol{y} \qquad \forall t \tag{2.1g}$$

$$\Big(\sum_{\tau=1}^{T} \boldsymbol{E}^{T-\tau}(\boldsymbol{H}^+\boldsymbol{y}_\tau^+ - \boldsymbol{H}^-\boldsymbol{y}_\tau^-) - (\boldsymbol{M}_1 + \boldsymbol{M}_2\boldsymbol{y})\Big)\Delta t + \boldsymbol{E}^T\boldsymbol{y}_0 = \boldsymbol{y}_T \tag{2.1h}$$