



Designing Pareto optimal electricity retail rates when utility customers are prosumers

Andrea Saumweber^{a,c,*}, Lars Wederhake^{a,b,c}, Gonalo Cardoso^a, Gilbert Fridgen^{b,d}, Miguel Heleno^a

^a Lawrence Berkeley National Laboratory 90R1121, Cyclotron Road, Berkeley, CA, 94720, USA

^b Project Group Business and Information Systems Engineering of the Fraunhofer FIT, Universitätsstraße 12, 86159 Augsburg / Wittelsbacherring 10, 95444, Bayreuth, Germany

^c FIM Research Center, University of Bayreuth, Wittelsbacherring 10, 95444, Bayreuth, Germany

^d SnT – Interdisciplinary Center for Security, Reliability and Trust, University of Luxembourg, 1855, Luxembourg

ARTICLE INFO

Keywords:

Ratemaking
Rate case
Prosumer
Utility
DER-CAM
Pareto optimization

ABSTRACT

Electric retail rate design is relevant to utilities, customers, and regulators as retail rates impact the utility's revenue as well as the customers' electricity bills. In California, regulators approve rate proposals by privately owned vertical integrated utilities. Approval, however, is subject to compliance with multiple, potentially conflicting objectives such as economic or environmental objectives. Additionally, retail rates are price signals that affect how customers use electricity services. When utility customers change their usage, they also impact the ratemaking objectives to which rates have been designed. This suggests a feedback loop, which is particularly pronounced with prosumers, as they can systematically optimize their interactions with the electricity system. Prevalent ratemaking methods may not deliver retail rates that are optimal for multiple objectives when customers are prosumers. We propose a novel ratemaking method that formalizes the problem of designing retail rates as a multi-criteria optimization problem and accounts for prosumer reactions through a simulation-based optimization approach. Through a fictive case study, we found that the resulting Pareto frontiers are useful in recognizing and balancing tradeoffs among conflicting ratemaking objectives. Additionally, our results indicate that prevailing retail rates in California are not Pareto optimal.

1. Introduction

The rapid diffusion of distributed energy resources (DERs), such as self-generation, demand-side management, storage, and controlling entities, substantially changes how utility customers interact with the electricity system (Abdelmotteleb et al., 2018). DERs have empowered customers to alter their load profiles economically while adhering to their consumption behavior. These customers, who we refer to as prosumers, can systematically reduce their electricity bills as they rationally optimize their load profile based on the rate structure to which they subscribed. In other words, the load profiles of utility customers continue to become more price-elastic.

However, the design of electricity retail rate structures has mainly been based on the assumption of static customers with short-term price-inelastic load profiles (Borenstein, 2015; Johnson et al., 2017; Schill et al., 2017; Seeto et al., 1997). Prosumers deploying DERs affect the

electricity system in the following three ways: first, affecting network planning and operation, in which technical changes may lead to either higher or lower network costs than in the scenario without DERs (Cosent et al., 2011). Second, they affect a utility's ability to recover and re-distribute costs from its customers (Eid et al., 2014). Third, they impact the amount of greenhouse gas emissions (GHG) as customer-sited DERs typically use low-carbon technology (Williams et al., 2012). The emergence of prosumers thus demands new or adapted methods for electricity rate design (Jargstorf et al., 2015; Picciariello et al., 2015; Pollitt, 2018) to reap opportunities and mitigate potential downsides. Designing efficient retail rates for prosumers is a wicked problem in a position of debate between regulators, utilities, and customers.

In this vein, previous research related to ratemaking methods either does not wholly accommodate multiple partially competing stakeholder goals (Abdelmotteleb et al., 2018) or does not adequately account for customer reactions (Belmans and Jargstorf, 2015); hence, systematic

* Corresponding author. Lawrence Berkeley National Laboratory 90R1121, Cyclotron Road, Berkeley, CA, 94720, USA.

E-mail address: andrea.saumweber@fim-rc.de (A. Saumweber).

<https://doi.org/10.1016/j.enpol.2021.112339>

Received 20 August 2020; Received in revised form 20 March 2021; Accepted 22 April 2021

Available online 9 June 2021

0301-4215/© 2021 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY license (<http://creativecommons.org/licenses/by/4.0/>).

optimization of rate structures (Abdelmotteleb et al., 2017) is required to design Pareto optimal rates for prosumers. Linking these design requirements, we contribute to the current research in two ways:

First, we present a novel ratemaking method that accounts for multiple stakeholder goals and prosumers' reactions simultaneously. In this paper, we focus on the setting where the predominant entity that charges retail rates is a vertically integrated utility (VIU) subject to a rate of return (ROR) regulation or synonymously a cost-of-service regulation scheme (Kopsakangas-Savolainen and Svento, 2010). Such locally regulated retail monopolies with potentially liberalized wholesale markets (Borenstein and Bushnell, 2015) are common in many parts of the world, especially in the United States (U.S.) of America, e.g., in California. In particular, the method is based on formulating retail rate design as a multi-criteria optimization problem where prices of rate components are optimized regarding acknowledged retail rate design principles. Prosumers' reactions are mapped into the multi-criteria optimization problem by adopting a simulation-based optimization (SBO) approach (Nguyen et al., 2014). Thereby, we identify the set of Pareto optimal rates and visually present the Pareto frontier. Reducing the design space of retail rates provides a basis for balancing conflicting ratemaking goals more systematically when utility customers are prosumers. This supports regulators in assessing and steering rate proposals by the utility. Second, we carry out a fictive case study in California, following the market design of VIUs under a ROR regulation scheme (Woo et al., 2003). The case study supports the discussion around the Pareto optimality in rate design and comparison with actual retail rates.

To deliver the two contributions, we structure our study as follows. In section 2, we describe the fundamental concepts of ratemaking. This includes the activities in rate cases, rate structure setups, retail rate design principles, the identified related academic contributions and tools in use by regulatory authorities. In section 3, we describe the ratemaking method, which includes the multi-criteria optimization problem, the simulation model, and the iterative nature of the SBO to identify and present Pareto optimal rates. In section 4, we present a fictive case study of a Californian utility. We describe the input data and present and discuss the results. Finally, in section 5, we summarize this study and derive implications for research and policymakers.

2. Background of rate design

2.1. General rate cases

Ratemaking is carried out every couple of years in proceedings before the regulator, known as general rate cases¹. Rate cases involve several interdependent activities aimed at reconciling the regulator's perspectives, the (private) investors owning the utility, and ratepayers. In general, the process of determining retail rates consists of three sequential actions. The first action is to determine the revenue requirement (RRQ), i.e., "the total amount of revenue the utility would need to provide a reasonable opportunity to earn a fair rate of return on its investment [...]" (Lazar, 2016). Second, the RRQ is allocated to different customer types (e.g., residential, commercial, industrial, transportation, etc.) and their subtypes. The allocation is based on the customers' contribution to the RRQ, that is, the costs they cause to the utility by using the electricity service. This contribution makes up the amount the utility is authorized to collect from the respective customer type. Third, utilities suggest methods for acquiring the authorized amounts. In particular, they propose rate structures for each customer type. For more detailed information on general rate cases in the U.S., we refer to Lazar (2016).

¹ Depending on the geography, rates cases are sometimes also synonymously termed rate case proceedings or the ratemaking process.

2.2. Rate structure setups

The third activity in a rate case requires the installation of rate structure setups that bill and also compensate customers for their usage or provision of the electricity service. There may be periodic charges and one-time payments (e.g., for connecting to or departing from the grid). Periodic charges are the focus of this study as they set out to reimburse the utility's costs for providing the electricity service. They specify rate components that assign a price tag to the metered physical unit. The most prominent periodic rate components are the *energy component* (\$/kWh), the *demand component* (\$/kW), and the *customer component* (\$), which is independent of the customer's usage or provision of the electricity service.

To date, compensation practices mainly rely on the energy component. For a complete taxonomy of compensation practices, e.g., various form of net metering, net purchase and sale, and fixed feed-in-tariffs, we refer to Hughes and Bells (2006). Especially in the U.S., *net metering* (\$/kWh) is prominent, which compensates the customer for any surplus kWh injected into the network at the utility's energy charge.

Each of the aforementioned rate components can be further differentiated by contextual factors (e.g., location and system load) and usage characteristics (e.g., volume and time of use). For example, time-of-use (TOU)-based rates have different pre-set prices for different time frames, e.g., during winter is more expensive than summer, or in the evening hours is more expensive than during nights.

2.3. Retail-rate design principles

The previous section describes a large design space for rate structures. Generally, research and practice-related literature rely on general principles to guide ratemaking decisions and evaluate rate structures. Those reflect different national and regional policy objectives as well as the interests of investors owning the local VIU and those of the customers. The principles are largely consistent in literature. The following is a summary of the principles found in Bonbright et al. (1992), Reneses et al. (2013)², Woo et al. (2014), and Rábago and Valova (2018).

1. *Economic efficiency*. This principle aims for rate structures that incentivize customers to behave in a way that is most efficient for the entire system in both short-term (e.g., reducing system load peaks) and long-term (e.g., incentivizing improved asset utilization to reduce capacity investments). To that end, rate structures should be cost-reflective, so they signal customers the (avoided) costs, and other benefits they cause through their actions.
2. *Financial sustainability*: This principle is concerned with the utility recovering all investments and operating costs under a fair rate of return (i.e., recover the RRQ). Furthermore, the utility's revenue and equally the rate structures should be stable over the years.
3. *Equity and fairness*: Generally, this principle asks for nondiscriminatory rate structures, i.e., charging customers equally for equal usage of the electricity service. However, in some contexts, discrimination is needed in favor of fairness (e.g., granting rebates to low-income customers, etc.).
4. *Environmental conservation*: This principle aims for rate structures that reduce GHG and facilitate the integration of intermittent renewable energies.
5. *Energy security and reliability*: This principle incentivizes that rate structures contribute to balancing locational demands and supplies. Furthermore, they should support reliability standards, for example, by promoting DERs to provide operating reserves.

² Reneses et al. (2013) further state the principle of additivity. This principle refers to unbundled electricity markets, in which all actors in the electricity supply chain must recover their costs through the end rate structure. As we focus on VIUs we omit this principle.

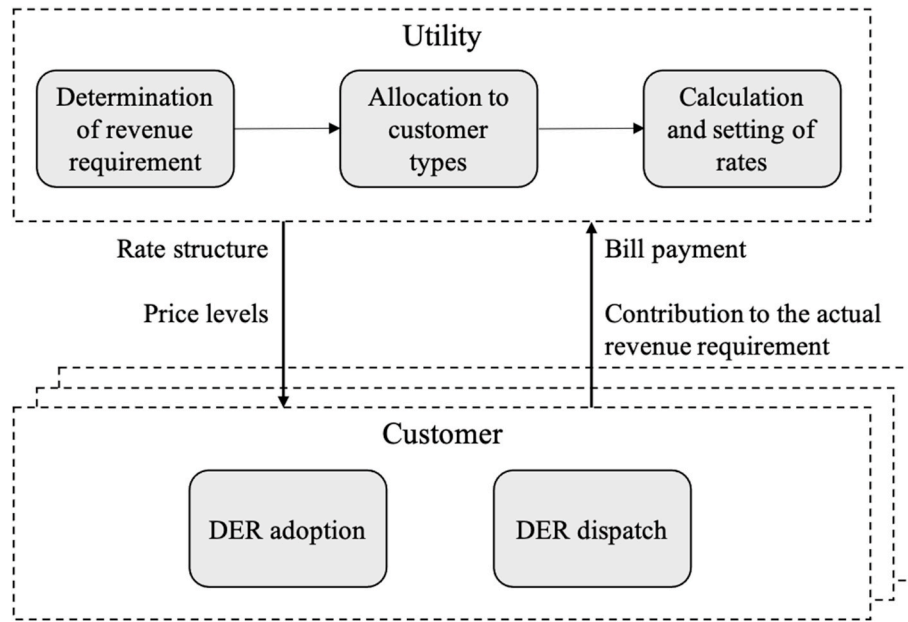


Fig. 1. Interaction of the utility's and customers' economic decision-making.

6. *Practicability and customer acceptance*: This principle requests rate structures that are feasible in application, consistent with the regulations in place, and acceptable to customers. This includes simple, understandable, and unambiguous rate structures along with transparent, stable, and traceable rate-setting methods.

2.4. Ratemaking tools used in the ratemaking methods

Ratemaking methods under ROR regulation need to consider the entire rate structure including both one-time and periodic payments. Therefore, there are various tools to support and accompany rate cases. Among others, there are tools supporting the identification of a fair ROR and tools helping to validate prudent investments and roadmaps, such as integrated resource plans (IRP). Simulation tools have a long history in public utility regulation, particularly with the California Public Utility Commission (CPUC) (Kahn, 1995). Recently, regulators such as CPUC also use simulation tools, e.g., the *Public Tool* helping in studying the effects of rate structures on various stakeholders (Public Utilities Commission of the State of California, 2014). The *Energy Efficiency Benefits Calculator*, an outcome of the National Action Plan for Energy Efficiency (NAPEE) facilitated by the Department of Energy (DoE) and the Environmental Protection Agency (EPA) of the U.S., sets out to study the impacts of energy efficiency programs on consumers, the utility, and society under a range of alternative mechanisms and policies (United States Environmental Protection Agency). While the latter has served for educational purposes, the former is a response to Assembly Bill 327 directing the Commission to set up a standard rate structure for renewable behind-the-meter DERs. The ratemaking tool was supposed to represent a common ground (same model, same assumptions, same limitations, etc.) for understanding the new rate structures following California's net energy metering (NEM). These prevalent ratemaking methods assume simplified relationships between rate structures and customer reactions (e.g., linear functions). However, rate structures give price signals to customers, influencing long-term customer decisions (e.g., DER adoption) and also short-term decisions (e.g., DER dispatch). Therefore, a change in the prices of retail components can affect customers' usage of the electricity service. In that case collected revenues and the RRQ may largely diverge, which would require recalculating the RRQ and setting rates differently. This feedback loop is presented in Fig. 1.

In academia, there are advancements in the Energy Efficiency Benefits Calculator as well as completely novel approaches to ratemaking. Proposals for new ratemaking methods are in line with recent calls by senior scholars in the field (Pérez-Arriaga (2013); Picciariello et al., 2015). FINDER is an enhanced academic version of the Energy Efficiency Benefits Calculator used as a tool to study the impact of model-endogenously influenced DER deployment and NEM on utilities and ratepayers (Cappers et al., 2019; Darghouth et al., 2016). Whereas FINDER incorporates features necessary to simulate the impact of rate structures, it does not support the optimization of rate structures concerning stakeholder goals, such as total system costs and average customer bills.

Despite the large body of work on novel ratemaking methods, custom tools have several shortcomings. For example, they do not adequately model multiple potentially competing stakeholder goals (Abdelmottaleb et al., 2018). In addition, such tools are often not sufficient in accounting for both short-term and long-term customer reactions influencing the RRQ (Belmans and Jargstorf, 2015) or do not optimize rate structures systematically (Abdelmottaleb et al., 2017).

This study sets out to help regulators overseeing the ratemaking process as part of the rate case by providing them with a method to optimally design rate structures. The method is capable of taking reactions by prosumers into account and balance potentially competing ratemaking goals, i.e., acknowledging the design principles outlined in section 2.3. We refer to this as designing Pareto optimal retail rates for prosumers. To the best of our knowledge, the two design requirements have only been studied in isolation, but no attempt has yet been made to link them.

3. Proposed ratemaking method

The proposed method primarily targets the third activity in a rate case, defining the rate structures. More precisely, we seek to find the Pareto optimal prices of rate components for prosumers regarding the retail rate design principles. We optimize the prices from a regulator's point of view, aiming to reconcile the stakeholders' interests.

The high-level design principles are quantified to serve as objective functions in a multi-criteria optimization model. Their values depend, inter alia, on simulated customer reactions on the rate structures. An SBO approach allows us to integrate the optimization model with

simulated prosumer reactions and dissolves the rate cases' sequential nature. The prosumer feedback loop, illustrated in Fig. 1, suggests this more iterative approach which is inherent to an SBO approach. The ratemaking method is as follows: Section 3.1 formalizes the multi-criteria optimization model. Section 3.2 outlines the simulation of the impact of customer reactions. Section 3.3 describes the algorithm used to solve the SBO.

3.1. Multi-criteria optimization model

The decision variables of the multi-criteria optimization model are the prices for the rate components, denoted by the vector p . This study targets the rate design principles of *economic efficiency*, *cost-reflectivity*, *equity and fairness*, and *environmental conservation* (cf. section 2.3). The three former principles usually experience priority in guiding the rate-making process (Bonbright et al., 1992; Reneses et al., 2013). Society and policy are increasingly concerned with environmental conservation. While not explicitly optimized, the remaining principles *energy security and reliability* and *practicability and customer acceptance* are reflected in

the model constraints and assumptions.

The first objective (1.1) targets economic efficiency, expressed as minimum total system costs. The total system costs include all market participants' annualized investment and operational costs minus the income. Formally, the total system costs are each customer's total costs plus the utility's (actual) RRQ minus the utility's revenue. Since the utility's revenue offsets customers' electricity bills, this objective corresponds to all private investments in DERs plus the utility's RRQ. The RRQ consists of fixed costs and costs that depend on customers' reactions on the rate structure. The customer-dependent costs are related to electricity purchases and capacity investments. Therefore, low electricity consumption and low prices are preferable. Variable spot prices in the wholesale market reflect marginal generation costs. Thus, it is beneficial if prosumers inject electricity to the grid when spot prices are higher than prices for compensation and withdraw electricity from the grid when spot prices are lower. Because high spot prices and high demand are correlated, this also balances the system load and defers capacity investments. For capacity investments, we consider the utility to comply with specified standards of service quality (compelled by the

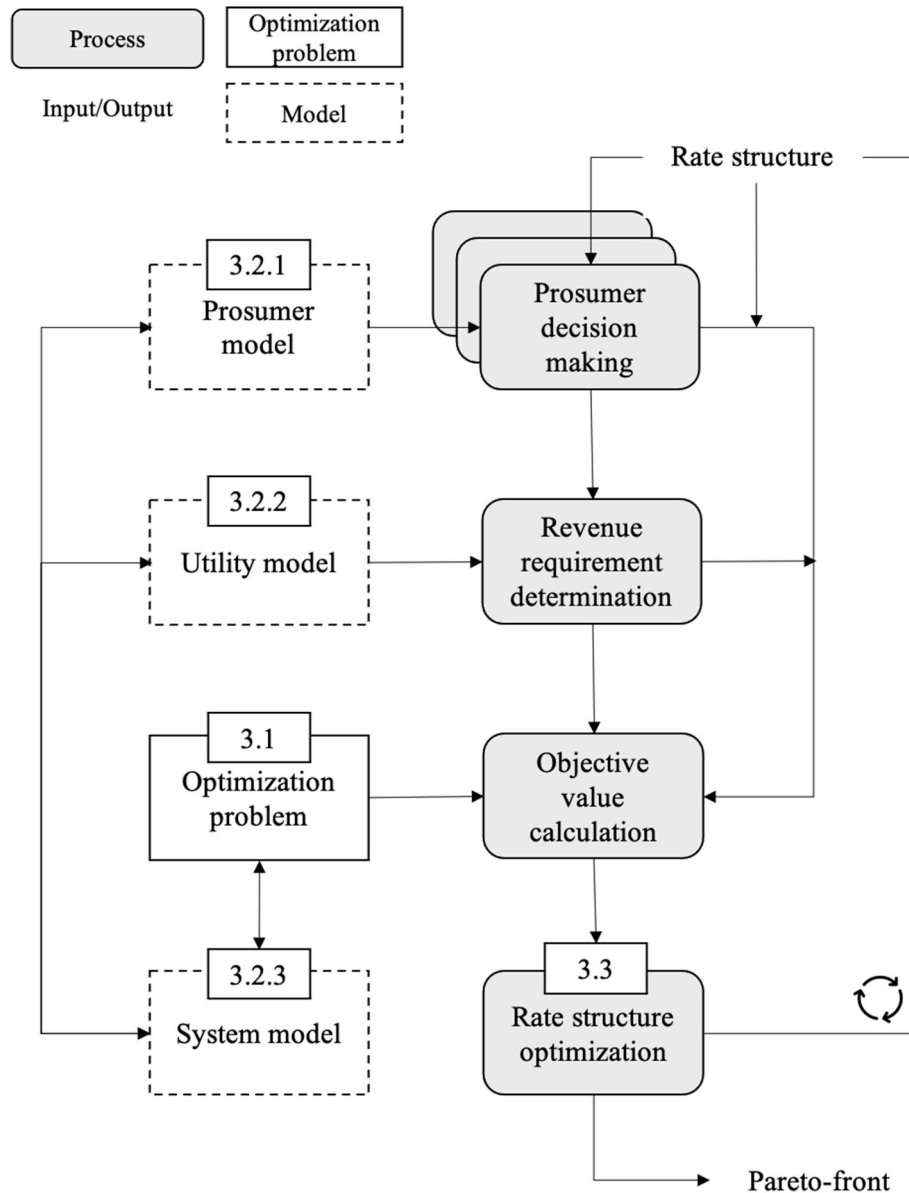


Fig. 2. Flowchart of the SBO approach for determining the effects of rate structures and the identification of Pareto optimal rates as well as the corresponding Pareto frontiers. The numbers reference the sections elaborating on the models and optimization steps.

regulator). This can refer to maintaining the current standard or upgrading on better standards. In either way, the utility ensures energy security and reliability without arranging over- or under-investments. We provide the notation for this section in Appendix A. The total system costs are given by TC , the total costs of customer i by $C_{total,i}$, the revenue requirement by RRQ_U , and the revenue by RV_U . Objective (1.1) is formalized as

$$TC(p) = \sum_i C_{total,i}(p) + RRQ_U(p) - RV_U(p) \quad (1.1)$$

The second objective (1.2) addresses financial viability, economic efficiency, as well as equity and fairness. We define the second objective as revenue neutrality, which sets out to minimize the absolute difference between the utility's revenue and RRQ, simply speaking the utility's profit or loss. In case of losses, shareholders will be unsatisfied, and customers might face higher rates in the upcoming year. In the case of profits, customers have paid too much for the service, which the regulator seeks to prevent. The objective also formalizes cost-reflectivity if all prosumers belong to the same customer type and are homogeneous (as in this study). The inelastic demand for static customers is predictable, and the rate structures for static customers are designed such that revenue equals the RRQ. Therefore, the utility makes no losses or profits through static customers; only prosumers can cause deviations from revenue neutrality. The deviation is a multiple of the costs caused by the individual prosumer due to the considered homogeneity. As mentioned in section 2.3, cost-reflective rate structures are economically efficient because they provide optimal price signals. They can also be perceived as fair and equitable. Cost-reflective rate structures are nondiscriminatory because equal electricity consumption or self-generation are charged or compensated equally. This can be perceived as appropriate when customers are homogeneous, apart from electricity consumption and self-generation, for example, having equal financial wealth. Furthermore, cost-reflectivity reduces cross-subsidies among customers (Dupont et al., 2014; Rodríguez Ortega et al., 2008). Cross-subsidies can generally be perceived as unfair. The deviation from revenue neutrality is denoted by RD_U , the revenue requirement by RRQ_U , and the revenue by RV_U . Therefore, the objective (1.2) is formalized as

$$RD_U(p) = |RRQ_U(p) - RV_U(p)| \quad (1.2)$$

The third objective (1.3) addresses environmental conservation formalized as GHG. DERs or conventional power plants emit GHG to cover electricity consumption. The amount of emitted GHG depends on the dispatched technologies and the generated quantities. We distinguish between self-generated and purchased electricity from the market. Generally, self-generation is attributed to less GHG than purchased electricity due to dispatched fossil energy resources in the power mix. Thus, self-generation is preferred regarding objective (1.3), especially when many high-carbon technologies are dispatched to cover electricity consumption. We define a per kWh-GHG rate for self-generation and purchased electricity, described by ghg_{DER} and $ghg_{M,d,h}$. The latter reflects the average GHG rate of the technologies in the power mix. The respective quantities are given by $s_{DER,m,d,h,i}$ and $s_{U,m,d,h,i}$ where the indices denote the customer i , month m , day d , and hour h . Objective (1.3) is formalized as:

$$GHG(p) = \sum_i \sum_m \sum_d \sum_h \left(s_{DER,m,d,h,i}(p) \cdot ghg_{DER} + s_{U,m,d,h,i}(p) \cdot ghg_{M,d,h} \right) \quad (1.3)$$

In this study, we deliberately limit the design space and examine the Hopkinson rate structure combined with a net metering scheme. The Hopkinson rate consists in its purest form of an energy and a non-coincident capacity charge (Seeto et al., 1997). The Hopkinson rate structure and the net metering scheme are adequate to demonstrate how the proposed method helps to identify Pareto optimal combinations of multiple rate components. Furthermore, its simplicity accommodates

the principle of practicability and customer acceptance. The vector $p = (p_{kwh}, p_{kw})^T$ denotes the Hopkinson rate. Generally, the more rate components and differentiations a utility employs, the better it can tailor them for cost allocation and sending price signals to customers. Therefore, the results will be more efficient. Note that our method allows for any rate structure, and the regulator can assign a complexity measure to that rate structure in a similar vein as proposed by Salah et al. (2017). The regulator can then decide if the measure should be added as an additional goal or modeled as a constraint.

We minimize the three objectives above (1.1)–(1.3), while complying with price boundaries on the rate components, denoted by \underline{p} or \bar{p} respectively. Regulators can choose to adjust, add, or omit any objective function or constraint. The proposed multi-criteria optimization problem is as follows:

$$\min f(p) = (TC(p), RD_U(p), GHG(p))^T \quad (1)$$

$$\underline{p} \leq p \leq \bar{p} \quad (2)$$

3.2. Simulation model

The simulation model maps the effects of prosumer reactions on the ratemaking objectives. In particular, it considers the (inter-)actions of prosumers and their utility in the electricity system. The models for prosumers, utility, and electricity system are described in the following sections. First, we illustrate the workflow of the simulation in Fig. 2. The starting point is the rate structure, given to prosumers who make decisions about DER adoption and dispatch. The prosumers' decisions affect the utility's revenue and RRQ. This is the point where we resolve the sequential nature of the rate cases. The prosumers' reactions on the rate structure are captured in the first place, and only then, the RRQ is determined by the utility. This means that the actual impact of prosumer behavior on the utility's cost is regarded. The prosumer and utility model outputs are used to calculate the objective values of the multi-criteria optimization problem. The simulation further includes an electricity system model. It defines parameters and variables on an aggregated level, including the composition of the utility's customer portfolio and electricity market data. Such information is required for both the utility model and the multi-criteria optimization model.

3.2.1. Prosumer model

Prosumers are modeled to be economically rational and make optimal decisions under a given rate structure. In particular, they optimize their DER adoption and dispatch to minimize their total costs. This approach differs from diffusion models in which past adoption data are leveraged to predict customer reactions, for example, using regression models. In this study, we chose a Python-based implementation of DER-CAM for reasons of comprehensive scientific documentation (Armendáriz et al., 2017; Cardoso et al., 2014; Stadler et al., 2013), maturity, and availability. Note that this is not a limitation of the ratemaking method, and alternative prosumer models can be used. Stadler et al. (2014) provided a full account of modeling tools for prosumer reactions with regard to DER adoption (long-term) and DER dispatch (short-term). In addition, Rahimian et al. (2018) present a comprehensive overview of software dedicated to modeling such decision-making in (community) microgrids.

In this study, DER-CAM assumes prosumers to install solar PV and stationary battery storage systems whenever economically attractive. This occurs when annual savings from injecting energy to the grid creates reduced payments to the utility exceeding amortized investment as well as operations and maintenance costs for PV and storage. Prosumers minimize their total costs in particular, as expressed through equations (3)–(7). The electric balance is ensured through equation (11), and PV and storage constraints are reported in equations (12)–(17). Finally, the economic variables are linked via equations (8)–(10). The model can be

easily extended with additional DER-CAM features, such as peak shaving or demand shifting, electric vehicles, heat storage, solar thermal energy, and combined heat and power (CHP). Nevertheless, storage and PV cover self-generation and the ability to alter load profiles while adhering to the original behavior. Thus, it provides a realistic picture of prosumers. We provide the notation in [Appendix B](#).

a. Objective function

$$\min C_{total} = C_{ST} + C_{PV} + C_{elec} - V \quad (3)$$

$$C_{ST} = (C_{STfix} \cdot b_{ST} + C_{STvar} \cdot c_{ST}) \cdot \frac{r}{1 - \frac{1}{(1+r)^{L_{ST}}}} + \sum_{m,d,h} C_{STOM} \cdot o_{STm,d,h} \quad (4)$$

$$C_{PV} = (C_{PVfix} \cdot b_{PV} + C_{PVvar} \cdot c_{PV}) \cdot \frac{r}{1 - \frac{1}{(1+r)^{L_{PV}}}} + \sum_{m,d,h} C_{PVOM} \cdot o_{PVm,d,h} \quad (5)$$

$$C_{elec} = \sum_{m,d,h} s_{Um,d,h} \cdot P_{kWh} + \sum_m d_m \cdot P_{kW} \quad (6)$$

$$V = \sum_{m,d,h} e_{PVm,d,h} \cdot P_{kWh} \quad (7)$$

b. Economic constraints

$$c_{PV} \leq b_{PV} \cdot M_{PV} \quad (8)$$

$$c_{ST} \leq b_{ST} \cdot M_{ST} \quad (9)$$

$$d_m \geq s_{Um,d,h} \quad \forall m, d, h \quad (10)$$

c. Electric balance constraints.

$$s_{Um,d,h} + s_{PVm,d,h} + o_{STm,d,h} = i_{STm,d,h} + D_{Bm,d,h} \quad \forall m, d, h \quad (11)$$

d. PV constraints

$$o_{PVm,d,h} \leq c_{PV} \cdot n_{PVm,d,h} \quad \forall m, d, h \quad (12)$$

$$o_{PVm,d,h} = s_{PVm,d,h} + e_{PVm,d,h} \quad \forall m, d, h \quad (13)$$

e. Storage constraints

$$SOC_{STm,d,h} = SOC_{STm,d,h-1} \cdot (1 - \phi) + i_{STm,d,h} \cdot \eta_c - \frac{o_{STm,d,h}}{\eta_{dc}} \quad \forall m, d, h \quad (14)$$

$$c_{ST} \cdot \underline{SOC} \leq SOC_{m,d,h} \leq c_{ST} \cdot \overline{SOC} \quad \forall m, d, h \quad (15)$$

$$i_{STm,d,h} \leq c_{ST} \cdot \overline{CR} \cdot m_{STm,d,h} \quad \forall m, d, h \quad (16)$$

$$o_{STm,d,h} \leq c_{ST} \cdot \overline{dr} \cdot (1 - m_{STm,d,h}) \quad \forall m, d, h \quad (17)$$

3.2.2. Utility model

The utility model formalizes the financial view of the utility. The key inputs are the rate structure, financial data, market data, and customer

Table 1

Calculation of the revenue requirement.

<i>Rate Base (RB)</i>
Existing assets
+ Capacity investments
– Depreciation
= RB
<i>Operating Expenses (OPEX)</i>
Depreciation
+ Operations and maintenance costs
+ Electricity procurement costs
+ Taxes
= OPEX
<i>Revenue Requirement (RRQ)</i>
RB · ROR
+ OPEX
= RRQ

data. Financial data include utility assets and financial structure. Market data include all investment, operations and maintenance costs, the weighted average cost of capital (WACC), the assets' lifetime, the tax rate, and wholesale spot prices. Customer data include the customer portfolio, that is, the number of customers of each customer type and the customers' residual loads. Key outputs are revenue and the RRQ. The utility model includes calculations to determine the revenue, required capacity investments, purchased electricity, and the RRQ.

The calculation of revenue is straightforward. Electricity sold to and purchased from customers are compensated or charged at prevailing rate structures. The determination of the RRQ is a simplified representation of the first activity performed in a usual rate case. In general, utilities are allowed to recover their operating expenses (OPEX) and earn a regulated annual ROR on their rate base (RB). Therefore, the RRQ is defined as $RRQ_U = RB \cdot ROR + OPEX$. To account for cost components and their interdependencies in more detail while maintaining a reasonable level of abstraction, we orient our calculations at the *Energy Efficiency Benefits Calculator* ([United States Environmental Protection Agency, 2019](#)). The calculations are presented in [Table 1](#).

The RB accounts for capacity investments and depreciation. Analogous to the Energy Efficiency Benefits Calculator, we model the depreciation to be linear. The OPEX accounts for depreciation, operations and maintenance costs, electricity procurement costs, and taxes. As specified in the Energy Efficiency Benefits Calculator, we use the utility's WACC as ROR to calculate RB's return. Note that two former court cases in the USA⁴⁵ mandate the ROR to "be sufficient to allow the utility to attract additional capital under prudent management, given the level of risk that the utility business faces" ([Lazar, 2016](#)).

As for capacity investments, we assume that extensions to the network infrastructure are required whenever a single prosumer's peak demand or the peak demand of the system increases. In the former case, the costs for line expansions increase linearly with the peak demand, as with [Lo Prete and Hobbs \(2016\)](#). In the latter case, costs are proportional to the network peak, but in analogy to [Abdelmoteleb et al. \(2018\)](#), investments can only be made in 0.5 MW increments. We assume the utility of accepting all electricity sold by prosumers. The remaining customers' electricity demand is met by purchases on the wholesale spot market at prevalent locational marginal prices. Solely operations and maintenance costs are fixed and not influenced by prosumer reactions. We reiterate that the capacity investments and electricity procurement costs are calculated with the prosumers' actual reactions on the rate structure.

3.2.3. System model

The system model specifies market participants and the environment in which they interact. Key specifications are the composition of the

customer portfolio, the amount of GHG per kWh of PV and the market's power mix, and wholesale spot prices. The system model further defines the calendar year, which is an input for all other models. In this study, the system model rests on a base level with the primary function of providing data to the customer model, the utility model, and the objective value calculations. This system model lends itself to further extension easily. For example, one may model the physical electricity network in the way as demonstrated by [Cardoso et al. \(2017\)](#).

3.3. Multi-objective optimization approach

In view of rate cases and public hearings, transparency is highly relevant for communication among stakeholders. Visualizing the Pareto frontier presents the full range of decision alternatives and thus supports transparency. This is preferred by decision-makers such as regulators ([Simon, 1966](#)) and helps to balance the tradeoffs between the potentially conflicting ratemaking objectives. Thus, we deliberately advocate a-posteriori-Pareto-optimization method ([Miettinen, 1998](#)) when the computational effort is justified. For this purpose, we apply methods that heuristically but simultaneously identify multiple non-dominated solutions widely spread across the Pareto frontier. In this vein, the methods of this class gradually elicit the Pareto frontier. The rougher the actual frontier, the more solutions are necessary to extract the frontier via approximate solutions. Methods that elicit the Pareto frontier, that is, all its constituent solutions in a single run, are termed population-based metaheuristics ([Boussaïd et al., 2013](#)).

One advantage of metaheuristics is that they are generally applicable, that is, the problem type and its properties (e.g., multimodal, (non-)convex, discontinuous frontiers) do not need to be known upfront. This is particularly important, as the structure of the Pareto frontier may be difficult to anticipate. This advantage also allows us to adjust assumptions on the models used for prosumers, utility, etc. Since the applicability and replicability of the proposed ratemaking are pivotal, we specifically examine the most intensively researched population-based metaheuristics. These are most often nature-inspired, such as multi-objective evolutionary algorithms (MOEAs) ([Zavala et al., 2014](#)), while alternative less established methods exist ([Talbi et al., 2012](#)).

We use the non-dominated sorting genetic algorithm II (NSGA-II) ([Deb et al., 2002](#)). This algorithm serves as a benchmark for continuous multi-objective problems with few objectives in many studies ([Coello et al., 2004](#); [Li and Zhang, 2009](#); [Tan et al., 2019](#); [Zhang and Li, 2007](#)). [Zhou et al. \(2011\)](#) considered this algorithm a quasi-standard for problems with only a couple of objectives. Generally, [Zavala et al. \(2014\)](#) find it "the most popular [MOEA] in current use" and, more specifically, NSGA-II has been applied particularly frequently to energy engineering and economic problems ([Delgarm et al., 2016](#); [Dhanalakshmi et al., 2011](#); [Murugan et al., 2009](#); [Wen et al., 2015](#)). Nevertheless, a comprehensive evaluation of all applicable algorithms is beyond the scope of this study, mainly because the proposed method allows the replacement of NSGA-II with other algorithms. For implementation, in this study, we used PyGMO 2 as a Python interface to the Pagmo 2 C++ library.

4. Case study and results

For demonstration purposes, we apply the ratemaking method to a fictive rate case of a Californian utility serving 19 different customer types. Note that rate structures are normally designed for customer types such as residential, commercial, agricultural, and street lighting.

The case study is arranged into 19 scenarios – one scenario per customer type. The customers of the particular type are prosumers and make decisions about DER adoption and dispatch. Customers who belong to other customer types have inelastic demand. We point out that the computation of Pareto optimal rate structures in isolated scenarios does not necessarily result in a holistic optimum of the multi-criteria optimization problem. This is because all customers would need to be

Table 2

Techno-economic data for PV and storage.

Economic and technological Data	Battery Storage	Photovoltaics (PV)
<i>a. Economic data</i>		
Fixed capital costs, \$	295.00	3,851.00
Variable capital costs, \$/kW(h)	193.00	3,237.00
Operations and maintenance costs, \$/kWh	0.00	0.25
Lifetime, years	5	20
<i>b. Technological data</i>		
Minimum State of charge	0.30	
Storage maximum charge rate	0.10	
Storage maximum discharge rate	0.25	
Storage charging efficiency	0.90	
Storage discharging efficiency	1.00	
Electricity storage loss factor	0.001	

considered simultaneously as prosumers. However, with all customer types being prosumers, interaction effects emerge, and it would be difficult to conclude on the effects of individual prosumer reactions, especially on the utility's RRQ. For tractability, we decide to run one scenario per customer type. Section 4.1 presents the setting and the data of the case study, and section 4.2 displays the results including the Pareto frontiers, Pareto optimal rate structures, and the impact of rate structures.

4.1. Case setting and data

The case study takes place in California in 2017. The regulator strives to identify Pareto optimal Hopkinson rates to control a local utility placed at San Francisco Airport. The energy charge of the Hopkinson rate is constrained by $P_{kWh} \in [0 \frac{\$}{kWh}, 1 \frac{\$}{kWh}]$. This is a generous upper bound compared to the average retail rate prices in the United States whose 2017 maximum is at 0.26 \$/kWh ([State Electricity Profiles - Energy Information Administration](#)). The demand charge is constrained by $P_{kW} \in [0 \frac{\$}{kW}, 100 \frac{\$}{kW}]$ – far more than the maximum demand charge across U.S. utilities, which is 51.25 \$/kW ([McLaren et al., 2015](#)). The lower price boundary of 0.00 \$/kW(h) reflects the absence of the rate component. With that, the rate component can be declared as irrelevant if it is 0.00 \$/kW(h) in all Pareto optimal solutions. Further data assumed for customers, the utility, and the system are described in the following sections.

4.1.1. Customer data

The case study considers 19 residential and commercial customer types (full-service restaurant, hospital, large hotel, large office, medium office, midrise apartment, outpatient care, primary school, quick-service restaurant, residential base, residential high, residential low, secondary school, small hotel, small office, stand-alone retail, strip mall, super-market, and warehouse). The dataset contains hourly load profiles for those customer types at all typical meteorological year locations in the U.S., which are part of the third collection (TMY3) ([OpenEI DOE Open Data, 2019](#)). Within that dataset, residential customer loads are based on the Building America House Simulation Protocols ([Wilson et al., 2014](#)). The commercial customer loads are based on DOE commercial reference building models ([U.S. Department of Energy, 2020](#)). For statistical reference of the customer types by location, the dataset uses the DOE Residential Energy Consumption Survey (RECS) ([U.S. Energy Information Administration, 2020](#)). We refer to [Appendix C](#) for descriptions of the customer type's hourly load profiles at the chosen San Francisco Airport TMY3 location. The hourly loads are converted to the DER-CAM schedule ([DER-CAM Tools, 2019](#)) where a typical year is described by three representative day-types per month: weekday, weekend, and peak-day. The monthly peak day is the day with the observed maximum

Table 3
Financial and market data for the utility model.

Vertical Integrated Utility (VIU)	
a. Financial data	
Existing assets, \$	1,600,000,000.00
Equity (debt) share of rate base, %	50 (50)
b. Market data	
Weighted average cost of capital (WACC), %	9.00
Tax rate, %	40.53
Asset lifetime, years	30
Operations and maintenance costs, \$	14,191.00
Line investment costs, \$/kW	150.00
Network investment costs, \$/kW	3713.18
Network investment increment, kW	500

load. We use the remaining days to obtain typical weekday and weekend profiles by applying arithmetic means. The techno-economic data for PV and storage are retrieved from previous DER-CAM work (Groissböck et al., 2011; Stadler et al., 2014) and displayed the data in Table 2. Hourly profiles for the PV electricity output at San Francisco Airport TMY3 location are retrieved from the DER-CAM database that draws data from the National Renewable Energy Laboratory (2005). Finally, we consider customers to invest at an interest rate of 3%, corresponding to the 15-year fixed mortgage rates in 2017 (Freddie Mac, 2019).

4.1.2. Utility data

We obtain all required data from the VIU-tailored version of the Energy Efficiency Benefits Calculator (United States Environmental Protection Agency, 2019), introduced in section 3.2.2, and add data not provided by the Energy Efficiency Benefits Calculator, that is, line and network investments. We use the same data as Lo Prete and Hobbs (2016) for line investments, and as Abdelmotteleb et al. (2018) for the network investment increment. Network investment costs were approximated using the ratio of existing assets and the system peak in the base-case scenario. The base case scenario assumes that all customers have inelastic demand. Thus, its system peak is the maximum of all customers' aggregated static loads. We present the utility data in Table 3.

4.1.3. System data and initialization

The customer portfolio composition is based on Cardoso et al. (2017), who report realistic shares of the total energy consumption per customer type. The listed shares are multiplied with an initial total energy consumption of 2,365,200 MWh, which is retrieved from the VIU case of the Energy Efficiency Benefits Calculator (United States Environmental Protection Agency, 2019). The second column in the table in Appendix C presents the composition of the customer portfolio.

Furthermore, the system data includes wholesale spot prices and the hourly GHG rate of the power mix. We use the 2017 locational marginal prices at the node of San Francisco Airport for wholesale spot prices (CAISO, 2019). For the GHG rates, we combine the hourly supply data of each day in 2017 with the static emission data of eleven different generation technologies. The supply data are provided by the Californian Independent System Operator (CAISO). We report the static emissions data. The emissions data is in line with the tracking method published by CAISO (Hundiawale, 2016) and reported in Appendix C. This CAISO method uses a time-static constant of GHG for imports that approximate unspecified electricity imports from interstate transmission connections. This makes up only 15% of California's electricity mix (Kaatz and Anders, 2016). We eventually calculate the weighted mean of the generation technology-specific emissions to obtain GHG rates. We convert all system data to match the DER-CAM schedule described above. The peak days for each dataset are the maximum observed values. Thus, the monthly maxima are the highest customers' loads, the highest spot prices, and the highest GHG. In this case study, we assume that all peaks

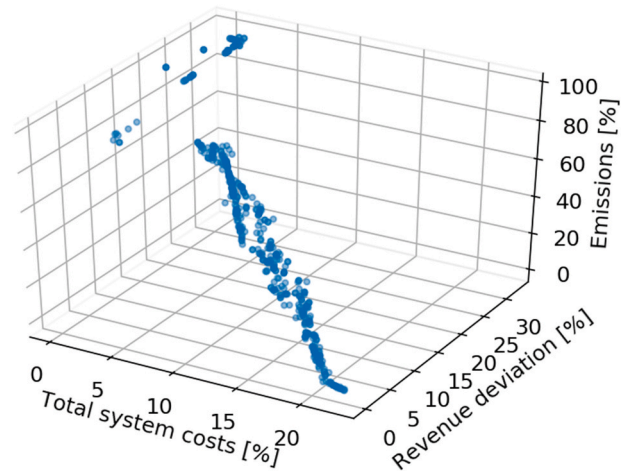


Fig. 3. Pareto frontier for the customer type midrise apartment.

coincide: all customers' maximum demands occur at once, and the highest spot prices and GHG coincide with the system peaks. The year 2017 determines the number of each day type per month.

The algorithm is equipped with the decision vector of the prices for the energy charge and demand charge, all three objectives, the direction of optimization, and constraints (i.e., price limits). Regarding the two exogenous parameters to MOEAs (number of generations, size of initial population), we set the number of generations to 100 and the number of initial solution candidates to 500. This parameterization matches the ranges of the benchmark studies (Tan et al., 2019). Note that when choosing more complex rate designs, both numbers might diverge from the ones chosen here.

4.2. Results and discussion

This section presents the results for the customer type *midrise apartment*. Our findings for the other scenarios are very similar and can be excluded for clarity. We examine the Pareto frontiers in section 4.2.1 and the associated Pareto optimal rate structures in section 4.2.2. Supplemental analyses in section 4.2.3 provide more details on the impact of rate structures on the ratemaking objectives, prosumers, and utility. To highlight tradeoffs between the three objectives and other metrics, we normalize all values dependent on the rate structure to a 0–100% range. 0% corresponds to the minimum value, and 100% to the maximum value occurred during the iterations of the NSGA-II algorithm.

4.2.1. Pareto frontier

The Pareto frontier includes solutions with total system costs between 0% and 25%, deviations from revenue neutrality between 0% and 35%, and GHG between 0% and 100%. Rate structures that generate objective values above these thresholds are always Pareto dominated. This rules out rate structures that lead to higher total system costs and larger deviations from revenue neutrality. In contrast, there exist superior rate structures for the entire range of possible GHGs. The Pareto frontier itself reveals very divergent solutions, e.g., the following vectors $(TC, RD, GHG)^T$ are Pareto optimal: $(14\%, 6\%, 58\%)^T$, $(22\%, 0\%, 1\%)^T$, and $(2\%, 33\%, 96\%)^T$. The Pareto frontier is depicted in Fig. 3.

The results reveal that the ratemaking objectives can be reconciled to some extent, but tradeoffs remain. This emphasizes the relevance of considering multiple objectives in the ratemaking process, in particular environmental objectives.

In this regard, the Pareto frontier provides support for the rate-making process. For one, it helps regulators to balance conflicting ratemaking goals more systematically by reducing the design space to

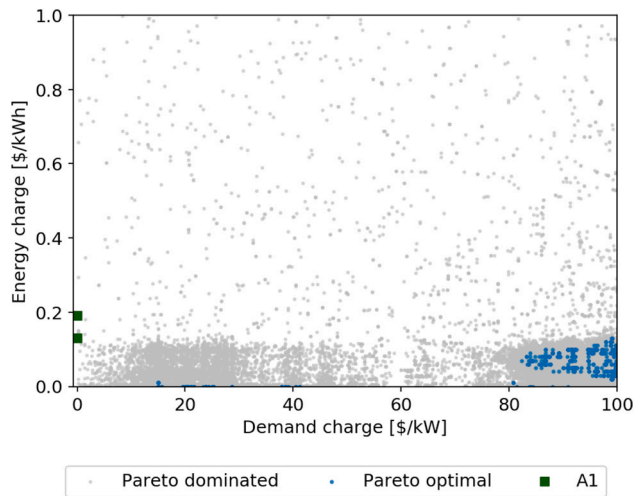


Fig. 4. Comparison of rate structures for the customer type midrise apartment.

superior rate structures. For another, it provides objective and measurable information that can be included in the ratemaking policy and directives or used for discussions among stakeholders, such as in public hearings. However, it should be taken into account that the Pareto optimal solutions are very divergent, which might make it difficult to find compromises among stakeholders. Other methods, such as scenario-based analyses like the FINDER tools, only evaluate pre-selected rate structures. While being subjective and incapable of making conclusions about optimality, the pre-selected rate structures may already show convergence.

4.2.2. Pareto optimal rates

All Pareto optimal rate structures consist of energy charges that are less than or equal to 0.13 \$/kWh and demand charges that are more than or equal to 15.02 \$/kW. If the threshold for the energy charge is exceeded or the threshold for the demand charge is undercut, the rate structure will be Pareto dominated. We compare these results to empirical rates we find in ratebooks for the respective customer types (Pacific Gas and Electric, 2020). The energy charges are relatively high, while demand charges are usually just at or below the threshold and rarely offered for residential customers. For example, this is manifested by the rate structure A1 applicable to residential customers (0.13 \$/kWh in winter and 0.19 \$/kWh in summer). Fig. 4 gives an overview of the rate structures mentioned. The Pareto optimal rate structures are displayed in blue, the Pareto dominated rate structures that occurred during the iterations of the NSGA-II algorithm in grey, and the empirical rates in green.

The results indicate that the demand charge is an important rate component, even in the residential sector. This is consistent with the findings and qualitative arguments found in literature (Hledik, 2014; Passey et al., 2017). However, the results also suggest that prevailing rate structures in California are not Pareto optimal and need to be adapted to satisfy the ratemaking objectives outlined. Of course, TOU rates are an available option that may mitigate the downsides of energy-only rate structures. To that end, examining time-variant pricing as an extension of this study appears to be very interesting.

4.2.3. Impact of rate structures

Total system costs increase with the energy charge, while no clear correlation to the demand charge is apparent. The deviation from revenue neutrality increases with the energy charge and decreases with the

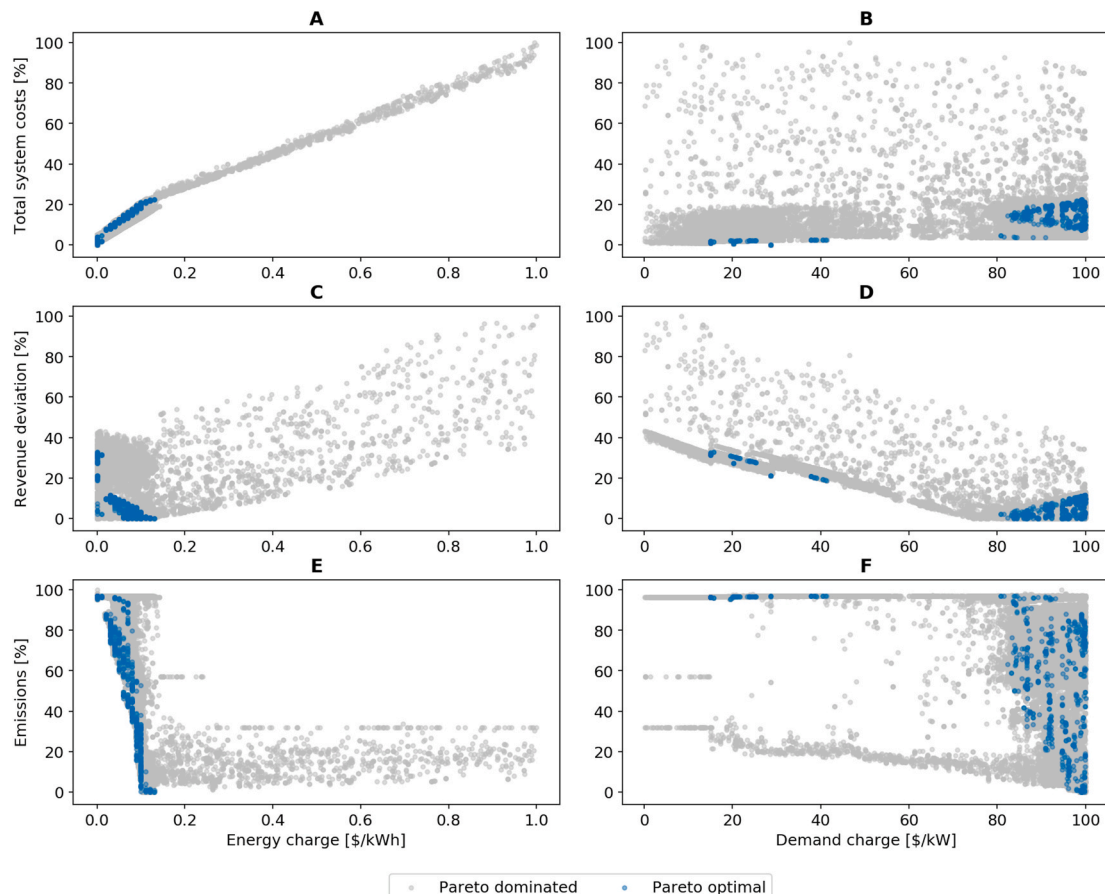


Fig. 5. Objective values in relation to the rate structures for the customer type midrise apartment.

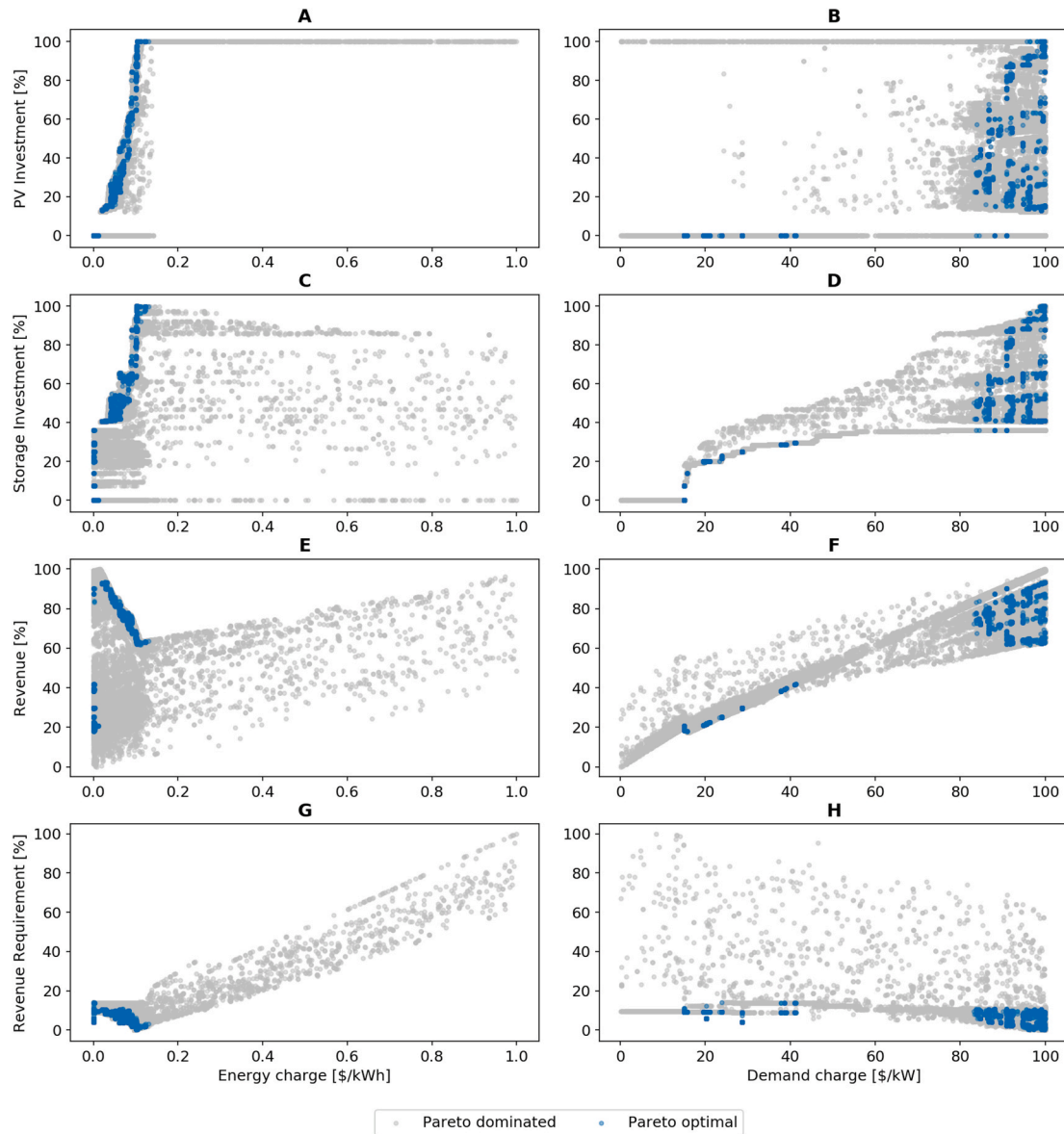


Fig. 6. Rate effect values in relation to the rate structures for the customer type midrise apartment.

demand charge. GHG begin to drop sharply as the energy charge increases but stagnate above the threshold of 0.13 \$/kWh. The impact of the demand charge on GHG depends on the energy charge with which it is combined. When the energy charge is below 0.13 \$/kWh, the demand charge seems to be uncorrelated. When the energy charge is above 0.13 \$/kWh, GHG are reduced with the demand charge. Fig. 5 displays the objective values in dependence on the rate components. The blue data points are Pareto optimal and the grey data points are Pareto dominated. In Fig. 5f, the rate structures with an energy charge lower than 0.13 \$/kWh form the line at 100% plus the cluster on the right. Rate structures with energy charges above 0.13 \$/kWh lead to the curved line in the bottom half.

PV investments increase with the energy charge, while there is no discernible trend in demand charges. With regard to the energy charge, PV investments converge quickly to a maximum level that is reached around the threshold of 0.13 \$/kWh and stagnate thereafter. Storage investments are significantly driven by the demand charge and only secondary by the energy charge. In fact, a demand charge of 14.98 \$/kW or higher is required to incentivize any storage investment. The revenue generally increases with both rate components. However, for some rate

structures, roughly those with demand charges above 50 \$/kW, the revenue declines with the energy charge towards the threshold of 0.13 \$/kWh. The RRQ decreases or stagnates with the energy charge, approximately up to the threshold, and then rises again. If the demand charge is increased, the RRQ slightly decreases. Fig. 6 displays the correlation of the rate structure with DER investments and the utility's financials. The blue data points are Pareto optimal and the grey data points are Pareto dominated.

Evidently, the thresholds for the energy charge and the demand charge are about the same in all subsections of section 4.2. This can be attributed to DER investments. Due to savings from self-generation and the net metering compensation, PV investments become more profitable with the energy charge. At 0.13 \$/kWh, prosumers have presumably reached their maximum required PV capacity and do not invest further. Storage is worthwhile for the prosumer if the savings from peak reduction cover the investment costs. Apparently, the break-even point lies where the demand charge reaches 14.98 \$/kW. The impact on the utility and the objectives values results from the interactions of our model explained in detail in section 3.1. The thresholds arise because different effects dominate after the investment stop in PV and

investment start in storage.

The relations between the rate structure, prosumers' reactions, and the utility's financials demonstrate that the three key activities of rate cases are highly interdependent. They should not be followed strictly in the sequence of determining the RRQ, apportioning it to the customer types, and eventually designing rate structures. The emerging inaccuracies can easily lead to discrepancies in meeting the identified ratemaking objectives. This finding is consistent with previous discussions on ratemaking methods, which were motivated by the fact that feedback loops have rarely been considered (Picciariello et al., 2015; Pollitt, 2018).

Furthermore, we find that the effects of the individual rate components cannot be determined in isolation. For example, promoting PV by increasing the energy charge is only effective up to a certain threshold and always requires a demand charge to result in a Pareto optimum. It is necessary to consider the rate components altogether and modify them simultaneously. Figs. 5 and 6 give a detailed and quantitative description of the impacts of modifying rate components. Therefore, our findings complement previous research and public studies (Fridgen et al., 2018; Jargstorf et al., 2015) that remain interpretative and perform ceteris paribus analyses when discussing the impacts of modifying only one rate component at a time.

5. Conclusion and policy implications

This paper formulated retail rate design as a multi-criteria optimization to support regulatory decisions around ratemaking in presence of prosumers, aligned with the current practices of cost-of-service. Our findings confirm previous research stating that sequential methods based on static customer loads, such as those used in rate cases, are ill-suited. This is because prosumers influence investments in customer-side DERs, while investments in those DERs lead to a feedback loop and change utilities' costs and revenues. These assumptions may be the reasons for our results indicating that prevailing rate structures in California are not Pareto optimal. They include comparatively high energy charges and too low or even no demand charges for some customer types. This emphasizes the need for policymakers to adopt improved ratemaking methods and initiate a revision of current rate structures.

We show the relevance of considering multiple objectives in the ratemaking process, particularly environmental targets, which lead to different levels of DER penetration. The objectives, approved by policymakers, should reflect all stakeholders' interests and be transparent throughout the entire ratemaking process. We further demonstrate that prosumers' reactions to changes in rate structures can be ambiguous and only be poorly predicted, for example, promoting PVs by increasing the energy charge is only effective up to a certain threshold. Therefore,

prosumer reactions must be modeled precisely and simulated comprehensively during the ratemaking process. Moreover, reducing the design space to only Pareto optimal rate structures and visualizing the resultant Pareto frontiers supports regulators in balancing tradeoffs among conflicting objectives. The quantitative measurement of policy objectives and other metrics, such as PV investments, captures the interplay between DER adoption and the ratemaking process. This provides objective and tractable information that can be used in discussion during the ratemaking process (e.g., public hearings), policy and directives. The proposed ratemaking method is an interesting way to study further model extensions (e.g., a distribution network model including power flow analysis), alternative regulatory frameworks, and its practical implementation in rate cases.

CRedit authorship contribution statement

Andrea Saumweber: Formal analysis, Software, Conceptualization, Visualization, Writing – original draft. **Lars Wederhake:** Conceptualization, Data curation, Investigation, Validation, Writing – original draft, Writing – review & editing. **Gonçalo Cardoso:** Conceptualization, Project administration. **Gilbert Fridgen:** Funding acquisition, Supervision. **Miguel Heleno:** Resources, Validation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

During a large part of the research activities associated with this paper, Gilbert Fridgen was Deputy Director of the Project Group Business & Information Systems Engineering of the Fraunhofer FIT, Germany, Deputy Director of the FIM Research Center, Germany, and Professor at the University of Bayreuth, Germany. We gratefully acknowledge the Luxembourg National Research Fund (FNR) and PayPal for their support of the PEARL project “P17/IS/13342933/PayPal-FNR/Chair in DFS/Gilbert Fridgen” that made this paper possible. We gratefully acknowledge the financial support of the Kopernikus Project “SynErgie” by the BMBF – Federal Ministry of Education and Research, Germany and the project supervision by the project management organization Projektträger Jülich (PtJ). The authors would like to acknowledge the Microgrids R&D and the Advanced Grid Modeling Programs of the U.S. Department of Energy - Office of Electricity, for the support granted to this work.

Appendix A

Table A. 1
Sets, variables, parameters of the multi-criteria optimization problem.

Notation of the multi-criteria optimization problem	
a. Indices	
$i \in \{1, \dots, N\}$	Customer index
$d \in D_m$	Days per month
$h \in \{1, \dots, 24\}$	Hours per day
$m \in \{1, \dots, 12\}$	Month per year
b. Decision Variables	
$p = (p_{kWh}, p_{kW})^T$	Rate structure, (\$/kWh, \$/kW)
c. Other Variables	
C_{totali}	Customer cost, \$
GHG	System greenhouse gas emissions, t-CO ₂ -eq
RD_U	Deviation from the revenue neutrality of the utility, \$
RRQ_U	Revenue requirement of the utility, \$

(continued on next page)

Table A. 1 (continued)

Notation of the multi-criteria optimization problem	
a. Indices	
RV_U	Revenue of the utility, \$
$SPV_{h,i}$	Electricity used from PV, kWh
$S_{U,h,i}$	Electricity purchased from utility, kWh
TC	Total system costs, \$
d. Parameters	
gh_{DER}	Greenhouse gas emissions of PV, t-CO ₂ -eq/kWh
$gh_{M,d,h}$	Greenhouse gas emissions of purchased electricity, t-CO ₂ -eq/kWh
\underline{p}	Lower bound of the rate structure
\bar{p}	Upper bound of the rate structure

Appendix B

Table B.1

Parameters of the customer model.

Input parameters	
a. Indices	
$d \in D_m$	Days per month
$h \in \{1, \dots, 24\}$	Hours per day
$m \in \{1, \dots, 12\}$	Month per year
b. Customer loads	
$D_{Bm,d,h}$	Electricity demand, kWh
c. Utility and market data	
p_{kW}	Demand charge, \$/kW
p_{kWh}	Energy charge, \$/kWh
r	Interest rate
d. PV parameters	
C_{PVfix}	Fixed PV costs, \$
C_{PVOM}	PV operations and maintenance costs, \$/kWh
C_{PVvar}	Variable PV costs, \$/kW
l_{PV}	PV lifetime, years
M_{PV}	Maximal required PV capacity, kW
n_{PV}	Normalized PV output, kWh/kW
e. Storage parameters	
\bar{c}_r	Storage maximum charge rate
C_{STfix}	Fixed storage costs, \$
C_{STvar}	Variable storage costs, \$/kWh
C_{STOM}	Storage operations and maintenance costs, \$/kWh
\bar{d}_r	Storage maximum discharge rate
l_{ST}	Storage lifetime, years
M_{ST}	Maximal required storage capacity, kWh
\overline{SOC}	Storage maximum state of charge
\underline{SOC}	Storage minimum state of charge
ϕ	Electricity storage loss factor
η_c	Storage charging efficiency
η_{dc}	Storage discharging efficiency

Table B.2

Variables of the customer model.

Variables	
a. Costs	
C_{elec}	Costs for electricity purchases from utility, \$, non-negative
C_{PV}	Costs for PV installation and operation, \$, non-negative
C_{ST}	Costs for storage installation and operation, \$, non-negative
C_{total}	Total electricity costs, \$, non-negative
V	Return from electricity exports to utility, \$, non-negative
b. Utility purchases	
d_m	Peak demand, kW, non-negative
$S_{Um,d,h}$	Electricity purchased from utility, kWh, non-negative
c. PV variables	
b_{PV}	PV purchase decision, binary

(continued on next page)

Table B.2 (continued)

Variables	
cpv	PV installed capacity, kW, non-negative
$epvm,d,h$	Electricity exports, kWh, non-negative
$opvm,d,h$	PV output, kWh, non-negative
$spvm,d,h$	Electricity used from PV, kWh, non-negative
<i>d. Storage variables</i>	
b_{ST}	Storage purchase decision, binary
c_{ST}	Storage installed capacity, kWh, non-negative
$istm,d,h$	Storage input, kWh, non-negative
$m_{STm,d,h}$	Mode of charge/discharge, binary
$ostm,d,h$	Storage output, kWh, non-negative
$SOC_{STm,d,h}$	Electricity stored in storage, kWh, non-negative

Appendix C

Table C.1

Descriptive data for the 19 customer types.

Customer type	Number	Total electricity consumption [kWh]	Maximum electricity demand [kW]
Full-service restaurant	172	307,311.67	53.77
Hospital	1	9,174,734.64	1,388.98
Large hotel	3	2,483,061.12	422.83
Large office	1	6,157,183.96	1,503.09
Medium office	42	685,228.10	204.93
Midrise apartment	152	228,854.06	51.94
Outpatient care	26	1,257,271.14	275.18
Primary school	171	858,597.91	288.72
Quick-service restaurant	277	191,240.94	32.14
Residential base	37,153	7,814.30	1.96
Residential high	11,046	10,513.65	2.70
Residential low	178,372	4,036.60	0.93
Secondary school	9	2,778,030.44	1,032.75
Small hotel	67	576,142.22	110.47
Small office	4,580	63,085.90	15.69
Stand-alone retail	404	274,418.61	69.90
Strip mall	199	272,151.39	68.47
Supermarket	26	1,672,328.72	309.05
Warehouse	1,293	242,142.84	70.06

Table C.2

Greenhouse gas emissions by source.

Greenhouse gas emissions by source	g CO ₂ -eq/kWh
Geothermal	38
Biomass	25
Biogas	11
Small hydro	13
Wind total	9
Solar PV	32
Solar Thermal	13
Nuclear	66
Thermal	525

References

- Abdelmotteleb, I., Gómez, T., Reneses, J., 2017. Evaluation methodology for tariff design under escalating penetrations of distributed energy resources. *Energies* 10 (6), 778. <https://doi.org/10.3390/en10060778>.
- Abdelmotteleb, I., Gómez, T., Chaves Ávila, J.P., Reneses, J., 2018. Designing efficient distribution network charges in the context of active customers. *Appl. Energy* 210, 815–826. <https://doi.org/10.1016/j.apenergy.2017.08.103>.
- Armendáriz, M., Heleno, M., Cardoso, G., Mashayekh, S., Stadler, M., Nordström, L., 2017. Coordinated microgrid investment and planning process considering the system operator. *Appl. Energy* 200, 132–140. <https://doi.org/10.1016/j.apenergy.2017.05.076>.
- Belmans, R., Jargstorf, J., 2015. Multi-objective low voltage grid tariff setting. *IET Gener., Transm. Distrib.* 9 (15), 2328–2336. <https://doi.org/10.1049/iet-gtd.2014.1165>.
- Bonbright, J.C., Danielson, A.L., Kamerschen, D.R., 1992. *Principles of Public Utility Rates*, second ed. Public Utilities Reports, Arlington, Vir, p. 700.
- Borenstein, S., 2015. The Private Net Benefits of Residential Solar PV: the Role of Electricity Tariffs, Tax Incentives and Rebates. NBER Working Paper, p. 21342.
- Borenstein, S., Bushnell, J., 2015. The US electricity industry after 20 Years of restructuring. *Annu. Rev. Econ.* 7 (1), 437–463. <https://doi.org/10.1146/annurev-economics-080614-115630>.
- Boussaïd, I., Lepagnot, J., Siarry, P., 2013. A survey on optimization metaheuristics. *Inf. Sci.* 237, 82–117. <https://doi.org/10.1016/j.ins.2013.02.041>.
- Californian Independent System Operator. CAISO electricity prices. <http://www.caiso.com/TodaysOutlook/Pages/Prices.aspx>. (Accessed 7 September 2019) accessed.
- Cappers, P., Satchwell, A., Gorman, W., Reneses, J., 2019. Financial impacts of net-metered distributed PV on a prototypical western utility's shareholders and ratepayers. *Energies* 12 (24), 4794. <https://doi.org/10.3390/en12244794>.
- Cardoso, G., Stadler, M., Bozchalui, M.C., Sharma, R., Marnay, C., Barbosa-Póvoa, A., Ferrão, P., 2014. Optimal investment and scheduling of distributed energy resources with uncertainty in electric vehicle driving schedules. *Energy* 64, 17–30. <https://doi.org/10.1016/j.energy.2013.10.092>.
- Cardoso, G., Heleno, M., Mashayekh, S., Coignard, J., Arlt, M.-L., Reneses, J., Stadler, M., Eto, J., Koritarov, V., Levin, T., Reilly, J., 2017. Integrated Modeling Tool for

- Regulators: Distribution Grid Locational Performance Modeling: Developing a Foundational Integrated Modeling Tool for Regulators. Proof of Concept and Prototype.
- Coello, C.A.C., Pulido, G.T., Lechuga, M.S., 2004. Handling multiple objectives with particle swarm optimization. *IEEE Trans. Evol. Comput.* 8 (3), 256–279. <https://doi.org/10.1109/TEVC.2004.826067>.
- Cossent, R., Olmos, L., Gómez, T., Mateo, C., Frías, P., 2011. Distribution network costs under different penetration levels of distributed generation. *Eur. Trans. Electr. Power* 21 (6), 1869–1888. <https://doi.org/10.1002/etep.503>.
- Darghouth, N.R., Wiser, R.H., Barbose, G., Mills, A.D., 2016. Net metering and market feedback loops: exploring the impact of retail rate design on distributed PV deployment. *Appl. Energy* 162, 713–722. <https://doi.org/10.1016/j.apenergy.2015.10.120>.
- Deb, K., Pratap, A., Agarwal, S., Meyarivan, T., 2002. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* 6 (2), 182–197. <https://doi.org/10.1109/4235.996017>.
- Delgarm, N., Sajadi, B., Delgarm, S., Kowsary, F., 2016. A novel approach for the simulation-based optimization of the buildings energy consumption using NSGA-II: case study in Iran. *Energy Build.* 127, 552–560. <https://doi.org/10.1016/j.enbuild.2016.05.052>.
- DER-CAM Tools | Building Microgrid. <https://building-microgrid.lbl.gov/der-cam-tools>. (Accessed 5 December 2019).
- Dhanalakshmi, S., Kannan, S., Mahadevan, K., Baskar, S., 2011. Application of modified NSGA-II algorithm to combined economic and emission dispatch problem. *Int. J. Electr. Power Energy Syst.* 33 (4), 992–1002. <https://doi.org/10.1016/j.ijepes.2011.01.014>.
- Dupont, B., Jonghe, C. de, Olmos, L., Belmans, R., 2014. Demand response with locational dynamic pricing to support the integration of renewables. *Energy Pol.* 67, 344–354. <https://doi.org/10.1016/j.enpol.2013.12.058>.
- Eid, C., Reneses Guillén, J., Frías Marín, P., Hakvoort, R., 2014. The economic effect of electricity net-metering with solar PV: consequences for network cost recovery, cross subsidies and policy objectives. *Energy Pol.* 75, 244–254. <https://doi.org/10.1016/j.enpol.2014.09.011>.
- Fridgen, G., Kahlen, M., Ketter, W., Rieger, A., Thimm, M., 2018. One rate does not fit all: an empirical analysis of electricity tariffs for residential microgrids. *Appl. Energy* 210, 800–814. <https://doi.org/10.1016/j.apenergy.2017.08.138>.
- Gas, Pacific, Electric, 2020. Tariffs: current gas and electric rate schedules, preliminary statements, rules and forms. <https://www.pge.com/tariffs/index.page>. (Accessed 17 May 2020) accessed.
- Groissböck, M., Stadler, M., Edlinger, T., Siddiqui, A., Heydari, S., Perea, E., 2011. The First Step for Implementing a Stochastic Based Energy Management System at Campus Pinkafeld. *E-Nova International Congress*, 2011.
- Hledik, R., 2014. Rediscovering residential demand charges. *Electr. J.* 27 (7), 82–96. <https://doi.org/10.1016/j.tej.2014.07.003>.
- Hughes, L., Bell, J., 2006. Compensating customer-generators: a taxonomy describing methods of compensating customer-generators for electricity supplied to the grid. *Energy Pol.* 34 (13), 1532–1539. <https://doi.org/10.1016/j.enpol.2004.11.002>.
- Hundiwal, A., 2016. Greenhouse gas emission tracking methodology. <http://www.caiso.com/Documents/GreenhouseGasEmissionsTracking-Methodology.pdf>. (Accessed 7 September 2019) accessed.
- Jargstorf, J., Jonghe, C. de, Belmans, C., 2015. Assessing the reflectivity of residential grid tariffs for a user reaction through photovoltaics and battery storage. *Sustainable Energy, Grids and Networks* (1), 85–98, 3.
- Johnson, E., Beppler, R., Blackburn, C., Staver, B., Brown, M., Matisoff, D., 2017. Peak shifting and cross-class subsidization: the impacts of solar PV on changes in electricity costs. *Energy Pol.* 106, 436–444. <https://doi.org/10.1016/j.enpol.2017.03.034>.
- Kaatz, J., Anders, S., 2016. The role of unspecified power in developing locally relevant greenhouse gas emission factors in California's electric sector. *Electr. J.* 29 (9), 1–11. <https://doi.org/10.1016/j.tej.2016.10.008>.
- Kahn, E., 1995. Regulation by simulation: the role of production cost models in electricity planning and pricing. *Oper. Res.* 43 (3), 388–398. <https://doi.org/10.1287/opre.43.3.388>.
- Kopsakangas-Savolainen, M., Svento, R., 2010. Comparing welfare effects of different regulation schemes: an application to the electricity distribution industry. *Energy Pol.* 38 (11), 7370–7377. <https://doi.org/10.1016/j.enpol.2010.08.013>.
- Lazar, J., 2016. Electricity regulation in the US: a guide, Washington. <http://www.rapo.org/knowledge-center/electricityregulation>. (Accessed 16 August 2019) accessed.
- Li, H., Zhang, Q., 2009. Multiobjective optimization problems with complicated Pareto sets, MOEA/D and NSGA-II. *IEEE Trans. Evol. Comput.* 13 (2), 284–302. <https://doi.org/10.1109/TEVC.2008.925798>.
- Lo Prete, C., Hobbs, B.F., 2016. A cooperative game theoretic analysis of incentives for microgrids in regulated electricity markets. *Appl. Energy* 169, 524–541. <https://doi.org/10.1016/j.apenergy.2016.01.099>.
- McLaren, J., Seth, Mullendore, Laws, N., Anderson, K., 2015. Identifying Potential Markets for Behind-The-Meter Battery Energy Storage: A Survey of U.S. Demand Charges.
- Miettinen, K., 1998. A posteriori methods. In: *Nonlinear Multiobjective Optimization*. Springer, pp. 77–113.
- Murugan, P., Kannan, S., Baskar, S., 2009. NSGA-II algorithm for multi-objective generation expansion planning problem. *Elec. Power Syst. Res.* 79 (4), 622–628. <https://doi.org/10.1016/j.epr.2008.09.011>.
- National Renewable Energy Laboratory, 2005. National solar radiation data base. http://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/tmy3/by_state_and_city.html. (Accessed 5 December 2019) accessed.
- Nguyen, Anh-Tuan, Reiter, Sigrid, Rigo, Philippe, 2014. A review on simulation-based optimization methods applied to building performance analysis. *Applied Energy* 113. <https://doi.org/10.1016/j.apenergy.2013.08.061>.
- OpenEI Doe Open Data, 2019. Commercial and residential hourly load profiles for all TMY3 locations in the United States -. <https://openei.org/doe-opendata/dataset/commercial-and-residential-hourly-load-profiles-for-all-tmy3-locations-in-the-united-states>. (Accessed 5 December 2019) accessed.
- Passsey, R., Haghdadi, N., Bruce, A., MacGill, I., 2017. Designing more cost reflective electricity network tariffs with demand charges. *Energy Pol.* 109, 642–649. <https://doi.org/10.1016/j.enpol.2017.07.045>.
- Pérez-Arriaga, L.J., 2013. Regulation of the Power Sector. Springer, London, p. 728.
- Picciariello, A., Reneses, J., Frías, P., Söder, L., 2015. Distributed generation and distribution pricing: why do we need new tariff design methodologies? *Elec. Power Syst. Res.* 370–376.
- Pollitt, M.G., 2018. Electricity network charging in the presence of distributed energy resources: principles, problems and solutions. *EEE* 7 (1). <https://doi.org/10.5547/2160-5890.7.1.mpol>.
- Public Utilities Commission of the State of California, 2014. Order Instituting Rulemaking to Develop a Successor to Existing Net Energy Metering Tariffs Pursuant to Public Utilities Code Section 2827.1, and to Address Other Issues Related to Net Energy Metering.: CPUC, p. 98.
- Rábago, K.R., Valova, R., 2018. Revisiting Bonbright's principles of public utility rates in a DER world. *Electr. J.* 31 (8), 9–13. <https://doi.org/10.1016/j.tej.2018.09.004>.
- Rahimian, M., Iulo, L.D., Duarte, J.M.P., 2018. A review of predictive software for the design of community microgrids. *J. Eng.* 2018 (15), 1–13. <https://doi.org/10.1155/2018/5350981>.
- Reneses, J., Rodríguez, M.P., Pérez-Arriaga, L.J., 2013. Electricity tariffs. In: *Regulation of the Power Sector*. Springer, pp. 397–441.
- Rodríguez Ortega, M.P., Pérez-Arriaga, J.L., Abbad, J.R., González, J.P., 2008. Distribution network tariffs: a closed question? *Energy Pol.* 36 (5), 1712–1725. <https://doi.org/10.1016/j.enpol.2008.01.025>.
- Salah, F., Flath, C.M., Schuller, A., Will, C., Weinhardt, C., 2017. Morphological analysis of energy services: paving the way to quality differentiation in the power sector. *Energy Pol.* 106, 614–624. <https://doi.org/10.1016/j.enpol.2017.03.024>.
- Schill, W.-P., Zerrahn, A., Kunz, F., 2017. Prosumage of solar electricity: pros, cons, and the system perspective. *EEE* 6 (1). <https://doi.org/10.5547/2160-5890.6.1.wsch>.
- Seeto, D., Woo, C.K., Horowitz, I., 1997. Time-of-use rates vs. Hopkinson tariffs redux: an analysis of the choice of rate structures in a regulated electricity distribution company. *Energy Econ.* 19, 169–185.
- Simon, H.A., 1966. Theories of decision-making in economics and behavioural science. In: *Surveys of Economic Theory: Resource Allocation*. Palgrave Macmillan; Springer [distributor], New York, Secaucus, pp. 1–28.
- Stadler, M., Kloess, M., Groissböck, M., Cardoso, G., Sharma, R., Bozchalui, M.C., Marnay, C., 2013. Electric storage in California's commercial buildings. *Appl. Energy* 104, 711–722. <https://doi.org/10.1016/J.APENERGY.2012.11.033>.
- Stadler, M., Groissböck, M., Cardoso, G., Marnay, C., 2014. Optimizing distributed energy resources and building retrofits with the strategic DER-CAModel. *Appl. Energy* 132, 557–567. <https://doi.org/10.1016/j.apenergy.2014.07.041>.
- administration. <https://www.eia.gov/electricity/state/> (accessed 5 December 2019).
- Talbi, E.-G., Basseur, M., Nebro, A.J., Alba, E., 2012. Multi-objective optimization using metaheuristics: non-standard algorithms. *Int. Trans. Oper. Res.* 19 (1–2), 283–305. <https://doi.org/10.1111/j.1475-3995.2011.00808.x>.
- Tan, Y., Lu, X., Liu, Y., Wang, Q., Zhang, H., 2019. Decomposition-based multiobjective optimization with invasive weed colonies. *Math. Probl Eng.* 2019 (4), 1–18. <https://doi.org/10.1155/2019/6943921>.
- United States Environmental Protection Agency. National action plan for energy efficiency. <https://www.epa.gov/energy/national-action-plan-energy-efficiency>. (Accessed 6 December 2019) accessed.
- U.S. Department of Energy. Commercial reference buildings. <https://www.energy.gov/eere/buildings/commercial-reference-buildings>. (Accessed 19 August 2020) accessed.
- U.S. Energy Information Administration, 2020. Residential energy consumption survey (RECS). <https://www.eia.gov/consumption/residential/>. (Accessed 19 August 2020) accessed.
- Wen, S., Lan, H., Fu, Q., Yu, D.C., Zhang, L., 2015. Economic allocation for energy storage system considering wind power distribution. *IEEE Trans. Power Syst.* 30 (2), 644–652. <https://doi.org/10.1109/TPWRS.2014.2337936>.
- Williams, J.H., DeBenedictis, A., Ghanadan, R., Mahone, A., Moore, J., Morrow, W.R., Price, S., Torn, M.S., 2012. The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity. *Science (New York, N.Y.)* 335 (6064), 53–59.
- Wilson, E., Engebrecht Metzger, C., Horowitz, S., Hendron, R., 2014. 2014 building America House simulation Protocols. <https://www.nrel.gov/docs/fy14osti/60988.pdf>. (Accessed 19 August 2020) accessed.
- Woo, C.-K., Lloyd, D., Tishler, A., 2003. Electricity market reform failures: UK, Norway, Alberta and California. *Energy Pol.* 31 (11), 1103–1115. [https://doi.org/10.1016/S0301-4215\(02\)00211-2](https://doi.org/10.1016/S0301-4215(02)00211-2).
- Woo, C.K., Sreedharan, P., Hargreaves, J., Kahrl, F., Wang, J., Horowitz, I., 2014. A review of electricity product differentiation. *Appl. Energy* 114, 262–272. <https://doi.org/10.1016/j.apenergy.2013.09.070>.
- 15-Year Fixed-Rate Mortgages Since 1991 - Freddie Mac. <http://www.freddiemac.com/pmms/pmms15.html>. (Accessed 5 December 2019).

- Zavala, G.R., Nebro, A.J., Luna, F., Coello Coello, C.A., 2014. A survey of multi-objective metaheuristics applied to structural optimization. *Struct. Multidiscip. Optim.* 49 (4), 537–558. <https://doi.org/10.1007/s00158-013-0996-4>.
- Zhang, Q., Li, H., 2007. MOEA/D: a multiobjective evolutionary algorithm based on decomposition. *IEEE Trans. Evol. Comput.* 11 (6), 712–731. <https://doi.org/10.1109/TEVC.2007.892759>.
- Zhou, A., Qu, B.-Y., Li, H., Zhao, S.-Z., Suganthan, P.N., Zhang, Q., 2011. Multiobjective evolutionary algorithms: a survey of the state of the art. *Swarm and Evolutionary Comput.* 1 (1), 32–49. <https://doi.org/10.1016/j.swevo.2011.03.001>.