Retail Rate Structures for Electric Distribution Networks in Transition: A Case for Automation

BY BROCK MOSOVSKY AND STEVEN DAHLKE

Introduction

Clean energy technologies are increasingly being deployed on electric distribution systems and retail electricity pricing is evolving to support the transition. This evolution involves moving from rates characterized by flat energy charges and net metering policies for distributed energy resources (DERs) towards modern structures that more accurately reflect a utility's costs to supply and deliver electricity. These include time-of-use schedules, demand charges, feed-in tariffs (FITs) for over-generation by DERs, and other dynamic pricing signals. These modern rate structures provide economic signals that encourage energy consumption during periods when supply is abundant and discourage consumption during periods when demand is higher and grid resources are more constrained.

Historically, net energy metering (NEM) policies have been the dominant compensation mechanism driving renewable DER growth in the United States, the large majority of which has been small-scale solar photovoltaics.(1) NEM requires utilities to compensate excess production from customer-owned generation at the relatively static retail electricity price. Under this paradigm, small-scale (<1MW) solar generation has grown an average of 27% per year from 2014-2018, and currently provides 33% of all solar energy in the United States.(2) Clearly, NEM policies have been an effective tool to stimulate early investment in distributed clean energy; however, policymakers have begun to shift away from this model for future distribution systems.(3)

NEM becomes less efficient as DER penetrations increase to substantial levels. As this occurs, the grid can become oversupplied with a particular form of generation (e.g., solar). This decreases the marginal value of each kilowatt-hour generated and increases grid management costs to accommodate the excess energy. Such a scenario is now common in California where mid-day solar penetrations can be so great that more traditional generation resources are forced to ramp down their operation in response.(4) As distributed generation levels rise, compensating DERs at static retail energy rates is an increasingly inaccurate reflection of their marginal value. Moreover, the intermittency of these DERs requires the utility to provide backup capacity to satisfy customer demand when the sun is not shining or the wind is not blowing. In both cases, DER growth with static net metering compensation leaves utilities to make up the balance in a skewed equation of value.

The decentralized and intermittent grid of today is different from the centralized and dispatchable grid of previous decades. As a result, static electricity rates that once provided a simple and effective mechanism for suppliers to recuperate costs are becoming increasingly inefficient and detached from the evolving price dynamics in organized wholesale markets with increasing renewable penetrations.(5,6) For this reason, utilities are now tackling the problem of designing retail rates that incentivize and shape their customers' energy consumption to better align with periods when energy is more abundant. For customers, this could mean enacting behavioral changes that adjust their traditional patterns of electricity usage to take advantage of reduced costs during certain times of day. It could also mean employing "load shifting" technologies such as home batteries, electric vehicles, or smart thermostats to automate the shifting of electricity usage behind the meter and capitalize on periods of low retail prices. In either case, both the utility and the customer benefit economically: the utility by receiving demand profiles that are less costly to serve and the customer by reducing their monthly electricity bill.

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In the past, regulators typically pushed back on dynamic retail electricity pricing because of concerns with exposing customers to increased uncertainty in their energy bills.(7) Additionally, behavioral and psychological changes are notoriously difficult to effect. Today, however, the emergence of cost-effective battery storage is providing new impetus and feasibility to retail rate reforms. Distributed storage can overcome traditional psychological and regulatory barriers by automating changes in consumption patterns in response to new price signals. This includes arbitraging energy rates between periods with differing time-of-use prices, shaving peaks to reduce demand charges on monthly bills, and reducing exports in jurisdictions where compensation for excess renewable energy is only a fraction of the rate for electricity purchased from the grid. In this way, storage coupled with dynamic retail rates provide a promising path forward for electricity distribution networks in transition.

Insights

We propose two prerequisites for DER-focused retail rate design to be successful in uncovering the true economic value of these resources:

- Shifting of customer electricity demand from one period of the day to another must be automatable. Relying on behavioral changes alone will not result in sufficient adoption to effect systemic change.

- Utilities must understand how various rate structures will modify customer demand profiles, both at the individual customer level and in aggregate for a given penetration level of distributed storage. This requires advanced analytical modeling and optimization.

If the above prerequisites are met, retail rates themselves have the ability to "shape" or "mold" customer demand profiles to better align with periods when supply is abundant and associated costs to serve demand are low. The overall effect should be one of net economic benefit to both the utility and its customers: a rare win-win outcome.

To inform an example of how retail rates can be used to shape customer demand, consider first several relatively standard retail rate structures: time-of-use (TOU) rates, demand charges, and feed-in tariffs (FITs). TOU rates charge customers different amounts based on when electricity is consumed. They generally encourage customers to shift some of their energy consumption from periods of high prices to periods of low prices. A battery can derive value from TOU rates by arbitraging the rate schedule; that is, it can charge when prices are low and discharge when prices are high, saving the customer the difference between the two rates. Such rates may vary seasonally, by day of week, and/or by hour of day. Whereas TOU rates focus on energy volumes (kWh), demand charges bill a customer based on their maximum power consumption (kW). These too provide value to a battery insofar as it can discharge when the customer's native demand (demand in absence of any on-site generation or storage) is highest, reducing the maximum amount of power the customer must draw from the grid. This mode of operation is often referred to as "peak shaving". Finally FITs offer a third revenue stream for a battery in jurisdictions without NEM where compensation for energy exported to the grid is less than the retail rate the customer would pay to buy that energy back. Such a structure discourages export of electricity during periods when rooftop solar generates more electricity than the customer's demand, and batteries can "soak up" this excess energy, storing it for discharge later when needed. This avoids the loss in value that would result from sending the over-generation back to the grid, resulting in a net financial gain for the customer. For a more detailed discussion of modern retail rate structures and their use in conjunction with DERs and battery storage, see Faruqui 2018.(8)

Retail Case Study – Rooftop Solar, No Battery

With the above rate structures in mind, we examine the retail bill dynamics of a hypothetical commercial customer in California with a large rooftop solar installation and a demand profile that peaks sharply in the evening hours. Figure 1 illustrates hourly energy profiles for such a customer on a representative day in July. We analyze the case where the customer's retail rate schedule includes a two-period TOU-based energy rate (on-peak hours are shaded red in the figure), a demand charge calculated from the maximum demand in any hour, and a FIT that compensates electricity sent back to the grid at a rate significantly below the customer's retail energy rate. Additional details of the retail rate schedule analyzed are provided in Table 1.

RATE COMPONENT	SCHEDULE	RATE
ON-PEAK ENERGY	M-F, hour-ending 1200-2200	$0.23/kWh
OFF-PEAK ENERGY	M-F, hour-ending 0100-1100, 2300-2400 Sa-Su & holidays, all hours	$0.15/kWh
DEMAND	Maximum across all hours of billing cycle	$12/kW-month
SOLAR FIT	All hours, all kWh sent to grid	$0.10/kWh

Table 1. Example July rate schedule for a commercial customer in California.

As seen in the figure, the customer generates more solar energy than their native electricity demand in hours-ending 10 AM through 4 PM. In this example, the misalignment between the customer's native demand profile and that of the solar generation results in significant and frequent over-generation for photovoltaic systems of any appreciable size. Since there is no battery to consume the surplus energy, it must be sent back to the grid and the customer is compensated through the FIT at less than half the rate they would pay for energy during the on-peak period. This represents a significant loss of value compared to if they were able to consume that energy behind the meter to directly offset their demand.

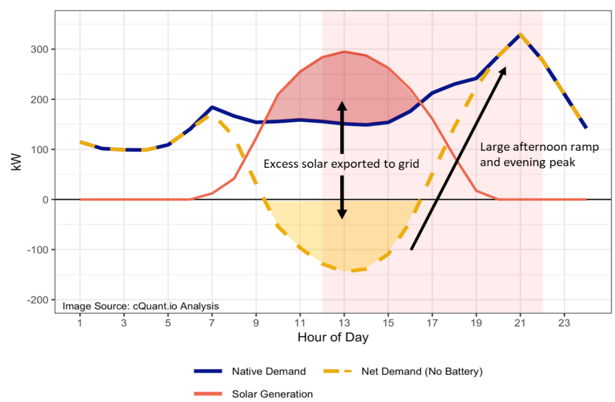

Figure 1. Hourly native demand, on-site solar generation, and net demand for a commercial customer in California with a late-evening peaking load on a representative day in July. Red shading denotes hours that correspond to the customer's on-peak TOU rate period. Surplus mid-day solar and a sharp peak in evening demand present economic opportunities for a battery relative to TOU rates, demand charges, and FITs.

The sharp evening demand peak seen in Figure 1 also represents a financial hurdle for the customer. It contributes an out-sized cost to the customer's energy bill for high levels of demand that persist for only a few hours of the day. In particular, the single highest hourly demand, occurring in hour-ending 9 PM, is more than 40 kW greater than the second-highest hourly demand. With a demand rate of $12/kW-month, the customer could save more than $500 on their monthly bill if they were able to reduce their usage in just this single peak hour of the day. Because of the potential for large bill savings by modifying demand in just a small number of hours, such "peaky" load profiles can provide a compelling value proposition for batteries when the appropriate retail rate structures are in place, as we will see in section on *Retail Case Study – Rooftop Solar With On-Site Battery* below.

Despite the misalignment of shaping relative to the customer's native demand profile, rooftop solar does provide significant value in this example by directly offsetting a good deal of mid-day energy consumption. Here, solar contributes more than a 35% reduction in the customer's July electricity bill (see Figure 3 below). However, the consistent mid-day overgeneration leaves value on the table because FIT compensation is so much less than the customer's retail energy rate.

Retail Case Study – Rooftop Solar With On-Site Battery

To understand how adding a battery could improve overall bill economics for the example customer introduced above we used an optimization model to compute optimal dispatch of an 800 kWh/200 kW battery system relative to the customer's native hourly load profile, their hourly solar generation, and all the retail rate components described in Table 1. Sized this way, the battery could store just under 20% of the customer's daily July energy usage and could discharge at roughly 2/3 of their peak demand. Figure 2 shows the resulting optimal charge and discharge pattern of the battery (solid light blue line) that minimized the

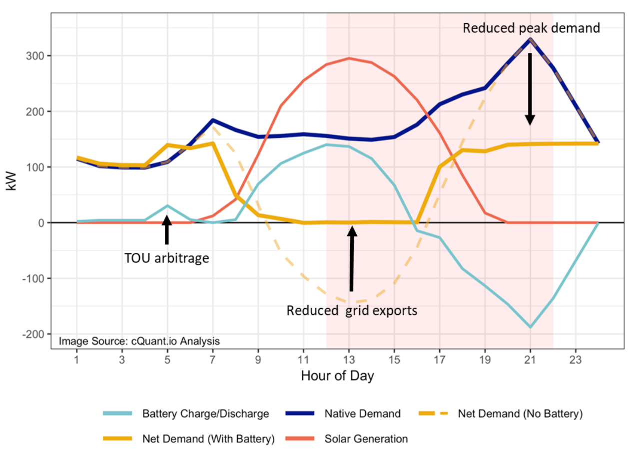

Figure 2. Optimal hourly battery operation relative to customer demand, solar generation, and retail rates including TOU, demand, and FIT components. The battery operates to avoid export of excess solar energy to the grid, reduce peak net demand, and arbitrage TOU schedules to the economic benefit of the customer, as seen by the solid yellow curve.

customer's total retail bill and the corresponding net demand purchased from the grid (solid yellow line). As seen in the figure, the battery's operation virtually eliminated the export of energy back to the grid and significantly reduced the peak net demand. The result was a 25% reduction in the total July electricity bill compared to the case of rooftop solar alone (see Figure 3).

In the example, the battery is able to derive value in three ways: by peak shaving to reduce demand charges, by reducing grid export to avoid economic losses from the low FIT, and by arbitraging the TOU schedule to capture the differential between on-peak and off-peak energy rates. This value is possible only because the retail rates compensate the battery for charging and discharging at very specific times. Combined with automation and optimization of the battery's operation, the two prerequisites of successful DER rate design we proposed above, the retail rates actually shape the customer's net demand. As a result, we see how application of a few simple and well-understood rate components can transform a customer's grid-based energy usage (net demand) in a way that benefits both the customer and the utility (see Table 2).

It is important to note that the battery's operation in our analysis is completely and automatically determined by the optimization model in response to the economic signals at play. Interactions between rate components can be highly complex, but an optimization model is designed to efficiently account for all these complexities when identifying the best outcome. Furthermore, the model guarantees that the outcome respects important constraints on battery operation, e.g., maximum charge/discharge rates, maximum energy storage capacity, etc. Such models will be key components of future utility rate design, as

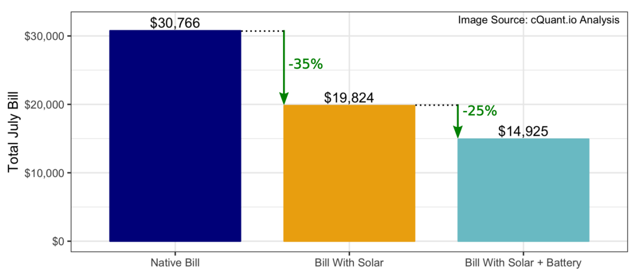

Figure 3. July electricity bill for a large commercial customer in California with only grid purchases (native bill), with rooftop solar, and with solar-plus-storage.

noted in prerequisite two above.

While the bill reductions shown in Figure 3 are striking, we do acknowledge several challenges with achieving such results in real-world applications. Technologies to automate battery operation in real-time are still in development; these are needed to satisfy the first prerequisite for DER-centric rate design noted above. Additionally, uncertainty in customer demand and solar production make perfect real-time optimization difficult to achieve, meaning actual battery operation may be suboptimal, providing less value to both the customer and the utility in practice than in theory. Finally, different customer load profiles will respond to the same rate structures in different ways, meaning there is no "one-size-fits-all" approach to rate specification. Further research and modeling is needed to better understand how retail rates can be designed to shape electricity consumption for individual customer sub-classes that share similar demand profile attributes. The above considerations notwithstanding, we believe there is great benefit to broadening current understanding of how batteries can respond to utility rate signals in an era of ever-increasing artificial intelligence and automation

EFFECT OF BATTERY	CUSTOMER BENEFIT	UTILITY BENEFIT
REDUCED PEAK NET DEMAND	Reduced demand charges	Reduced system peak, reduced system ramp
REDUCED EXPORT TO GRID	Increased value of rooftop solar generation	Mitigation of "Duck Curve" effects, reduced two-way power flow on grid, reduced system ramp
INCREASED OFF-PEAK CONSUMPTION	Bill reduction due to TOU rate arbitrage	Reduction in on-peak consumption, flatter system demand profile

Table 2. The mutual benefits of batteries to both utilities and their customers.

Conclusions

This analysis has shown how pairing a battery with rooftop solar can simultaneously accomplish several goals for both retail customers and utilities when battery operation is optimized to a relatively simple rate structure. Our case study analyzed the monthly electricity bill for a customer with on-site solar paying a basic two-level TOU energy rate plus demand charge in a jurisdiction without NEM. The cost-minimizing optimization eliminated two-way power flows, mitigated solar "Duck Curve" effects, reduced evening ramp, and lowered peak demand. In this way, combination of a battery with dynamic retail rate structures aligned the customer's economic incentives with the utility's operational goals.

We stress the importance of automating a battery's response to dynamic rate structures. This enables a customer to realize battery value without significant behavioral change. Furthermore, automation implies that the customer need not understand or even consider the complex analytics associated with optimizing battery operation. On the other hand, optimization modeling is important for utilities to understand before implementing next-generation rate design in a decentralized grid. Once a utility understands optimal battery operation relative to various rate structures, it can develop programs that fully abstract the analytical details away from the customer, simplifying the path toward adoption. Such programs could include providing incentives for or the direct provision of customer-sited batteries with solar installations, while the utility retains operational control of the battery. In exchange, the utility and customer would share battery value through avoided supply costs and retail bill savings, respectively.

The illustrative case presented in this article is just one example of the value from solar-plus-storage along with new rate structures. In general, analytics should be customized to customers' native demand profiles and a region's renewable energy production characteristics, along with a variety of dynamic rate structures. Further research should focus on how batteries respond to other rate structures, how responses interact with different load profiles to incent a desired load pattern, and how program design could be accomplished.

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