Residential Demand Response Program Design: Engineering and Economic Perspectives

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Abstract—There exists disagreement on how Demand Response (DR) programs should be designed. This is likely because people from different fields view DR differently. For example, some see DR as a mechanism to improve the economic efficiency of electricity markets while others see it as a new control variable that can enhance power system reliability and security. In this paper, we review the many options for harnessing residential electric loads for DR and consider the engineering and economic implications associated with three specific cases: (1) real time pricing, (2) dispatch-based control via an aggregator participating in wholesale markets, and (3) direct participation in energy markets. We develop both the engineering and the economic arguments for/against each option, and analyze them together in order to understand which options are most suitable for which applications. We find that the appropriate choice of DR program design depends on the DR program objective. Economic goals may be achieved through well-designed pricing and/or bidding mechanisms. Reliability is best achieved through dispatched-based programs. We illustrate our findings with several conceptual examples.

Index Terms—Demand Response, Residential Electric Loads, Dynamic Prices, Direct Load Control

I. INTRODUCTION

Electric power system operators generally assume that demand is exogenous and supply must be scheduled and, in real time, controlled to fulfill demand, at essentially whatever the operational cost. Demand Response (DR) programs are an attempt to make demand elastic. DR is defined by the US Department of Energy (DOE) as “a tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized” [1]. DR can provide a variety of benefits to power systems and power markets including reducing wholesale energy prices and their volatility [2], [3]; mitigating generator market power [2]; reducing the need for power system infrastructure expansion; reducing the use of peaking power plants that have high marginal costs [4] and are generally less efficient than other plants [5]; and improving grid reliability and power system flexibility, for example, via fast timescale energy balancing which is especially important in power systems with high penetrations of intermittent renewable resources like wind and solar power [6], [7], [8].

Engineers and economists often disagree on how DR programs should be designed. This is likely because the two fields view DR differently: economists see DR as a mechanism to make electricity markets more efficient while engineers see it as a new control variable that can enhance power system reliability and security. Clearly the engineering and economic issues are related; however, the way in which one views DR often affects one’s preference for either the first half of the DOE DR definition (dynamic electricity prices) or the second (incentive payments). Moreover, even within each of these categories there are many ways to design a DR program, and there is disagreement about which designs work best, or even what is meant by “best.”

In this paper, we assess options for harnessing residential electric loads for DR. We first summarize the options and then detail three examples, giving engineering and economic arguments for and against each. Our goal is to analyze the engineering and economic arguments side-by-side to better understand which DR program designs are best suited to which applications. We find that the economic and engineering arguments overlap to some extent, though the specific paths of argumentation differ and heavily rely on field-specific terminology. Therefore, our broader aim is to bring the engineer’s and economist’s perspectives together as a way to increase mutual understanding and, ideally, move towards some consensus on residential DR design and deployment.

We focus on residential loads for three reasons: (1) they may have advantages over larger loads, for example, reliable responses in aggregate and simple local dynamics/controls [9], [10]; (2) recent research has shown that the resource potential is large [10]; and (3) while many commercial and industrial load DR programs exist, there are few residential DR programs and so there is significant room for debate about the merits of different DR approaches.

II. OPTIONS FOR HARNESING LOADS

In this section, we first describe power systems and power markets in the US and Europe because an understanding of both systems is important for understanding possible residential DR program designs. We then summarize the engineering and economic view of DR and detail various types of residential DR programs. We end the section with a discussion of
some key issues in residential DR program design.

A. US and European Power Systems & Markets

1) US System: In deregulated power systems in the US, independent system operators (ISOs) run day-ahead and intraday energy and ancillary services (AS) markets. The amount of energy procured from generators is based on ISO load forecasts, and so the markets are one-sided: only the supply-side actively participates. Customers interact with the utilities who manage distribution systems, buy the energy procured in the market, and bill the customer. Retail electricity prices do not directly reflect time-varying wholesale energy prices. For example, residential customers usually pay fixed flat rates. These rates are designed to cover all of the fixed and variable costs incurred by the utility when supplying power to the customer. Rates must be approved by regulatory commissions, and so rate changes can take years. The US system is summarized in Fig 1.

2) European System: In Europe, the transmission system operator (TSO) is responsible for power system reliability and a separate market operator (MO) runs a a forward market, a day-ahead market, and an intraday market. To maintain system reliability, the TSO buys AS from generators. Balance groups (BGs), virtual aggregations that may contain generators and loads, must report their daily schedule to the TSO for system security analysis and they are committed to their reported schedules, with the option of adjustments on the intraday market. Two separate entities perform the roles of US utilities: (1) distribution system operators (DSOs) who maintain and operate the distribution system and interact with generators that connect at the distribution level and (2) energy retailers who bill customers, buy energy from the market, and pay fees to the DSO and TSO. Just as in the US, retail electricity prices in Europe do not directly reflect time-varying wholesale energy prices. The European system is summarized in Fig 2.

B. Engineering & Economic Views of DR

The power system is complex and nonlinear, and so it is difficult to accurately model. Moreover, it must operate given stochastic loads, intermittent renewables, and contingencies. Therefore, power system engineers rely on feedback control to ensure reliable and secure operation. DR is valued by engineers because it can be used as a control variable, in turn affecting long-term planning, short-term planning, and real-time power system operation. For example, DR can be used to defer upgrades of distribution systems, minimize procurement of energy/reserves in day-ahead markets, and provide real-time frequency support. Ultimately, the choice to use DR is an economic one; we must determine if the benefits outweigh the costs. However, it is often hard to ascribe realistic costs to power systems controls [11] and there are many different methods to compute the benefits associated with power system reliability and security [12].

DR is valued by economists because it can make power markets more competitive and therefore more efficient, improving social welfare. Several market failures exist in power markets: imperfect competition, imperfect information, externalities, incomplete markets, and the provision of reliability, a public good. DR can address some of these market failures. For example, DR increases demand elasticity, improving market competition. Additionally, DR programs provide customers with more information with which to make decisions beneficial to both themselves and the system. DR can also be used to differentiate between levels of reliability [13] so that customers can choose the level they want. This helps transform reliability from a public to a private good.

C. Types of DR Programs

DR programs can take many different forms. Here, we detail common program designs, classified in Table I. While many DR classifications already exist, e.g., [14], we define our own classification scheme that reflects how the consumer interacts with the system, i.e. via prices or dispatch commands.

Price-based DR programs can be split into three categories: time of use (TOU) electricity rates, dynamic electricity rates, and direct energy market participation. TOU rates follow schedules and encourage customers to shift electricity use to times when demand is usually low. Simple residential TOU rates are common in Europe where electricity is more expensive during the day than at night.

Dynamic electricity rates may be published day ahead or day of, and high prices are used to signify high expected
system load or power system issues. Dynamic pricing can be further split into peak pricing and Real Time Pricing (RTP). In peak pricing programs, DR events are called on a small number of the days in a year and on those days electric rates are raised during peak hours to encourage both shifting and shedding. In RTP programs, electricity prices may change, for example, hourly based on power system conditions. In the commercial and industrial sectors peak pricing programs are common, e.g., [15] and RTP programs exist [16]; however, they are both virtually nonexistent in the residential sector in both the USA and Europe with the exception of in pilot studies [17].

Loads participating directly in energy markets help set prices through quantity/price bidding, and then respond to the market clearing price. Typically only large industrial consumers are able to directly participate in energy markets, though Pacific Northwest National Laboratory developed an experimental market and demonstrated individual residential load bidding and response [18].

In dispatch-based DR programs, customers sign contracts with DR program coordinators that allow the coordinators to dispatch loads when needed. In exchange, customers receive incentive payments. Several types of dispatch-based DR programs exist. In remote switch-off programs, utilities can switch-off loads within some prior agreed-upon constraints. In Switzerland, utilities use “ripple control” to directly control residential water heaters via power line communication [19] and in California utilities offer remote air conditioner shut off programs [20]. In demand/capacity bidding programs loads offer demand reductions via price/quantity bids. If a bid is accepted the load must provide the reduction at the specified time. Similarly, loads participating directly in AS markets offer capacity and are dispatched within their capacity when needed.

Small loads, such as residential loads, would likely participate in bidding programs or wholesale markets via a load aggregator, which may be (1) a private company that provides the service of aggregation to the customers in exchange for a share of the DR profits, (2) the utility, (3) the retailer, or (4) the BG manager. For example, in several demonstration projects in California, utilities acted as aggregators to provide AS by cycling residential air conditioners [21], [22], [23]. In general, aggregators coordinate loads via dispatch signals.

**TABLE I: Classification of DR programs.**

<table>
<thead>
<tr>
<th>Price-based DR</th>
<th>Dispatch-based DR</th>
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<tbody>
<tr>
<td>Time of use (TOU) prices</td>
<td>Remote switch-off programs</td>
</tr>
<tr>
<td>Dynamic electricity prices</td>
<td>Demand/capacity bidding programs</td>
</tr>
<tr>
<td>peak prices</td>
<td>Direct ancillary services (AS) market participation</td>
</tr>
<tr>
<td>real time prices (RTP)</td>
<td>Aggregator programs</td>
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**D. Key Issues in DR Program Design**

DR design choices are usually made based upon the objective of the specific DR program, which may be primarily to address economic goals, engineering goals, or a combination of both. In addition to choosing between a price-based or dispatch-based program, a DR program designer must consider a number of issues:

- **Energy trading versus reliability provision**: Power systems provide two goods: energy and reliability. Reliability is defined by the North American Electric Reliability Council (NERC) as “the degree to which the performance of the elements of a bulk electric system results in power being delivered to consumers within accepted standards and in the amount desired” [24]. While energy is a private good, reliability is a public good because all customers connected to a system (with a few exceptions) receive the same level of reliability. Just like a generator, DR resources can trade energy, provide reliability, or both [3]; however, different DR program designs lend themselves to different capabilities, as discussed in the next section.

- **Frequency and lead-time of DR signals**: The frequency and lead-time of DR signals is related to the service provided. For example, to provide peak load shedding, loads usually receive a single DR signal a day to several hours ahead. However, to provide frequency response, loads needs to receive continuous high frequency signals and respond quickly and continuously.

- **Value of DR predictability/reliability**: Slow DR participating in energy trading does not need to be perfectly predictable since other power system resources could be called upon to compensate for unexpected DR results. However, most of these other resources take time to respond, so fast DR should be both predictable and reliable since other resources may not be able to respond in time to save the system.

- **Power system actor involvement**: Depending upon the goal of a DR program, a certain subset of power system actors will need to be involved. However, a DR program that does not consider all of the costs/benefits of each actor may be beneficial to some but negatively impact others [25]. For example, load responses to dynamic prices can negatively affect distribution systems [26].

- **Customer privacy**: The deployment of smart meters has raised privacy concerns with consumers, some of whom consider time series traces of their electricity consumption to be private information that they do not want to share with utilities or retailers. Whether or not DR is done via smart meters, participation in certain types of DR programs may require some exchange of information with other DR actors and so similar issues may arise.

- **Customer choice**: Different DR program designs give participants different levels of choice. For example, dispatch-based DR involves up front choice in contract design but little choice in real-time (unless some level of real-
time choice is part of the contract). Pricing and market outcomes give more real-time choice, though market outcomes can be undesirable by some customers.

- **Locational pricing:** Locational prices reflect actual system conditions including grid congestion and therefore incentivize the customer in the way that most benefits the system [26]. DR via locational marginal prices (LMPs) was investigated in [18] and recent FERC order #745 [27] requires that DR be paid at the wholesale LMP. However, with locational prices two customers with exactly the same economic preferences may face different prices because of grid congestion, an issue that they have little potential to affect, at least in the short-term. Customers may perceive this to be unfair.

- **DR baselines:** DR actions are usually measured relative to baselines, defined as an estimate of what load would have been without DR. Dispatch-based DR programs often require baselines for financial settlement. Unfortunately, good baseline models are difficult to develop and the simple models commonly used are error prone [28]. Moreover, some baselines can be prone to gaming [29]. However, there are ways to get around these issues including contracting for the baseline in advance [30].

- **Complexity and costs:** DR designs that involve large amounts of communication and/or high computational complexity may be more optimal in achieving program goals; however, these sorts of programs may not be practically implementable. In addition to infrastructure and computation costs, complex DR program designs can lead to high transaction costs, which are costs associated with economic interactions between many players and/or at very fast timescales.

### III. Residential DR Program Design Examples

We next consider three specific residential DR program design examples and analyze the engineering and economic considerations associated with each. In each case, we discuss the design’s suitability for both energy trading and reliability provision.

#### A. Example 1: Real time pricing

In this example, we assume customers receive real time prices from the retailer, utility, BG, ISO, or MO. Prices are formed based on the outcome of wholesale markets and sent to the loads on the same interval as the market closing, which could be hourly to practically instantaneously.

1) **Economist perspective:** Price signals give customers the opportunity to pursue their own optimization based on their own utility functions. This is efficient since the customer knows itself and its environment best. Because communication is one directional, customer are not obliged to make any private information public. Additionally, customers can individually take into account short- and long-term decisions in their price response which creates efficient consumption and investment behavior.

If we can assume that customers have quasi-linear utility functions (i.e. linear in one argument) resulting in an inverse demand function that is also a marginal willingness-to-pay function, and that they respond instantaneously to price signals with their optimal response when the real time market clears, then real time pricing has a chance to work. However, these assumptions may be not valid for two reasons: (1) consumers do not necessarily act as economists model them and (2) consumers cannot act instantaneously. With respect to the first concern, consumers do not necessarily maximize a well-defined utility function. They learn, sometimes slowly, and they do random things. That is, they may not respond to prices in the short-run and so one cannot expect DR to be quickly responsive. Therefore, reserves are needed to ensure power system security, especially in the case of emergency events.

The second concern requires a dynamic economic analysis. The key issue is that DR resources exhibit a lagged response to prices. Consider real time prices \( p \) at intervals of, say, 5 minutes. At time \( t \) there exists an excess demand

\[
X_t = L_t - G_t = E(p_{t-1}) + l_t - g_t + D(p_t),
\]

where \( L_t \) is the total system load; \( G_t \) is the total system generation; \( E(p_{t-1}) \) is the aggregate energy demand of DR resources based on the previous 5-minute price; \( l_t, g_t \) are unanticipated and un-price-responsive load and generation, respectively; and \( D(p_t) \) is the excess demand of all of the remaining system resources as a function of the current 5-minute price. Assume that operating reserves deal with \( l_t - g_t \) and so the price at \( t \) that clears the 5-minute market will solve

\[
D(p_t) + E(p_{t-1}) = 0
\]

Let \( D(p^*) + E(p^*) = 0 \) where \( p^* \) is the equilibrium price that would have cleared the market if DR was instantaneous and fully expressed in the market. To understand when this system is stable, we take a linear approximation around \( p^* \):

\[
D(p^*) + D'(p^*)(p_t - p^*) + E(p^*) + E'(p^*)(p_{t-1} - p^*) = 0
\]

which can be rewritten as

\[
p_t = p^* + \frac{E'}{D'} p^* - \frac{E'}{D'} p_{t-1}.
\]

This system is stable if and only if \( \left| \frac{E}{D'} \right| < 1 \). Therefore, this system becomes unstable if DR resources are more responsive than the resources that comprise \( D \). The price elasticity of DR resources depends on both the number and types of loads.

Fig. 3 illustrates this example by showing price behavior given three different linear mappings of the demand and supply functions [31]. As shown, even simple systems can experience price limit cycles and instabilities. If, as is likely, demand and supply functions are nonlinear, chaotic behavior is even more likely to occur [32]. We admit that these models are simplistic. Dampening effects through the inclusion of more information in the price signal are possible. However, the dissemination and processing of this information may increase transaction costs.
Fig. 3: Price dynamics given different linear mappings, \( L \), of the demand and supply functions. \( E \) is the line where \( p_t = p_{t-1} \), which is the equilibrium condition. Source: [31], p. 339.

2) **Engineering perspective:** Responding to price signals requires loads to be capable of making economic decisions and executing them, likely via optimization and controls software. For residential consumers to minimize their costs, they need good load models and forecasts of ambient conditions, energy usage, and so on. Since households solve relatively small individual optimization and control problems, they can use high fidelity models that take into account their specific preferences, while still keeping the problem computationally tractable. This allows customers to use the full flexibility of their resources.

Unfortunately, the responses of many loads to the same price signals can lead to synchronization resulting in power oscillations. DR via prices is a feedback loop in which the market closes, the prices are sent to the loads, and the loads respond, affecting the outcome at the next market closure. However, this is a delayed system in which the current actions of the loads are the result of prices set based on past loads. Feedback loops with significant delays, time varying plants (e.g., human behavior), nonlinearities, etc. can lead to unstable systems. As modeled in the previous section, DR via price could lead to power system instability, and related work has found similar results [33]. If loads do not behave as expected when participating in slow DR other resources can step in; however, problems may result if fast DR resources are unpredictable and unreliable because other resources may be too slow to compensate. Price response gives essentially no reliability guarantee and so it is best suited to energy trading via slow DR.

**B. Example 2: Dispatch-based control via an aggregator participating in wholesale markets**

In this example, an aggregator coordinates the behavior of loads to participate in an energy or AS market. Dispatch signals could be set point changes, power trajectories, on/off switching commands, etc. In fact, the signal could be prices if price responses are pre-determined and known by the aggregator who can simply translate control actions into prices.

1) **Economist perspective:** Dispatch-based control reduces financial risks for consumers, aggregators, and the system operator because it enables well-defined responses, which is especially important when DR provides reliability. Moreover, it is relatively easy to implement because the role of the system operator is unchanged, except that it now interacts with “virtual generators.” However, this set-up has several drawbacks. There are transaction costs associated with contract design and customers who value real-time autonomy over their energy consumption and/or privacy may not be willing to participate. The further away from real-time the contracts are negotiated the less they will capture the true flexibility of the resource. Moreover, unless the offered contracts cover all possible choices they will be incomplete contracts. DR contracts need to provide sufficient incentives for high consumer participation and result in profitable aggregator business models. Additionally, the contracts must be incentive compatible and therefore self-enforcing [34]. Finally, it is desirable to minimize the amount of private information required to enable contract enforcement, while at the same time encourage truthful statement of individual preferences. Mechanism design can address some of these issues.

2) **Engineering perspective:** Dispatch-based DR ensures predictable and reliable responses, which is useful for avoiding possible instabilities caused by price-based DR. Moreover, some consumers may not be interested in conducting their own optimization against dynamic prices and would rather contract with an aggregator for energy management of some of their loads. In this case, dispatch-based DR could be used for energy trading; however, it is most valuable for providing reliability.

A customer usually values the service electricity provides, not the electricity itself. Therefore, the ideal design of a dispatch-based DR program is to guarantee non-disruptive control so that the consumer does not notice any effects on the end use service, while extracting some useful service from the loads [8]. For example, the aggregator could have control of the operation of a customer’s water heater but guarantee that the water will always be between some temperature thresholds, and compensate the customer more for larger thresholds. In contrast to in the previous example, the majority of the DR intelligence now need only be in one place, at the aggregator, who can make intelligent choices when bidding in reserve markets, benefitting from the averaging of many different resources. Since control is via contract, DR can be reliable and certain and so the DR aggregation is more fully controllable. This means that dispatch-based DR is suitable for reliability procurement.

Since the aggregator controls the loads it has to understand their capabilities and how those capabilities change over time. Therefore, it is likely that some information will need to be sent to the aggregator periodically to ensure observability. Even with this information exchange the aggregator knows less about specific load capabilities unless all information is
exchanged in real-time, which is unrealistic. Additionally, for tractable optimization and control, the aggregator may have to use simplified models. So DR via aggregator may be less optimal than that via optimization by individual loads.

Fortunately, engineering tools including model reduction, system identification, state estimation, and control can help reduce communications, costs, and privacy issues, etc. For example, consider an aggregation of air conditioners (ACs) participating in a dispatch-based program to provide fast-DR such as load following. As shown in [35], for an aggregator to control the loads to closely track a signal while still staying within the the customers’ pre-determined temperature thresholds, an aggregator would ideally have the load send both its current temperature \( \theta \) and whether it is currently cooling or idle (i.e. on/off state, \( m \)) every few seconds in order to know the state of each load’s hybrid system model:

\[
\theta_{t+1} = f(\theta_t, m_t) \\
m_{t+1} = g(\theta_t, m_t),
\]

where \( m_t \in \{0, 1\} \) \( \forall t \). In addition, the aggregator would like to have additional information about each load, such as each air conditioner’s thermal parameters, with which to parameterize (5)-(6). However, if some or all of this information is unavailable the aggregator can still control the loads by using a model that captures aggregate system behavior:

\[
x_{t+1} = Ax_t + Bu_t \\
y_t = Cx_t
\]

where \( x \) keeps track of the number of ACs within discretized temperature intervals and on/off states, \( u \) is our control input, and \( y \) is the aggregate power consumption of the system. This linear model together with system identification and state estimation techniques and some offline and real-time information from the system allows us to track a power system signal. Depending upon the desired control performance, the aggregator may not need to receive any information from the loads in real-time. This issue is illustrated in Fig. 4.

### C. Example 3: Direct participation in energy markets

In this example, individual loads submit price/quantity bids to the system operator for optimization against all other resources in the market. The optimization is done via an Optimal Power Flow (OPF), a large optimization problem that takes into account the price/quantity bids of each resource along with the physical constraints of the power system. The timescale of the markets could hourly to practically instantaneously.

1) Economist perspective: Individual decentralized bidding processes should result in efficient electricity markets. Decentralized optimization achieves the same benefits as discussed in Example 1. However, there are several concerns with this approach. First, the communications and computing infrastructure needed is immense. With loads bidding individually, the communications required will lead to high transaction costs. Second, the implementation and enforcement of rules and responsibilities in the case of undesired market behavior, for example, lack of equilibrium, may not be an easy goal. Additional market products like hedging and insurance may be required to keep the market liquid. Third, even though complete decentralized market processes may reduce some market failures like imperfect competition, their impact on other market failures must be investigated. Finally, market rules would need to change to allow DR resources to bid their true capabilities and constraints. Specifically, resources that can shift energy consumption over time operate as storage units, which are energy constrained, and must be able to bid both in terms of power and energy.

2) Engineering perspective: As with Example 1, this example allows loads to do their own optimization. However, here they also need to develop their own bidding strategies. The price/quantity bids could reflect full DR capabilities since the loads themselves make the bids. However, the loads must be capable of making the bids, in addition to reacting based on the market outcomes. Both developing realistic strategies and then sticking to the commitments could be hard for some types of individual loads, especially those driven by human behavior. Aggregating loads together usually simplifies the bidding and control because it allows for averaging of stochastic behavior. However, in this example we do not consider aggregated bidding (which fits within Example 2).

One major advantage over Example 1 is that, market participation is via a contract and so load responses are more predictable and reliable than price responses. However, there are several drawbacks to this approach. Much communication is needed to send individual load bids to markets, especially for fast-timescale markets. Additionally, from a system perspective, it would be difficult and perhaps impossible to optimize the generator and load bids because the OPF including all bids and physical system constraints would be enormous and likely unsolvable. Current OPFs with only generator bids and system constraints approach the limits of modern computation systems [11].

### IV. Discussion

Table II summarizes the main engineering and economic pros and cons associated with each DR program design example. The choice of DR program design is a complex trade-off between market efficiency, customer choice, and system reliability. As the table shows, there is much overlap between the engineering and economic arguments for and against each example; however, the terminology used is different. For example, both perspectives list decentralized decision making as a pro: for engineers, it means better modeling, control, and optimization and, for economists, it means customers can make the decisions that they are better suited to make than any other entity. Additionally, price instability is a concern from both an economic and technical perspective, as are issues of complexity. Of course, some perspectives do differ, and the goal here is simply to clarify these differences so that they can be the basis for future discussions and debate.
The appropriate choice of DR program design depends on the objective, which is related to the timescale of the response. Both engineering and economic tools can be used to mitigate some of the disadvantages of the various designs, but we find that certain set-ups have inherent limitations for certain applications. For example, reliability provision via fast DR may require dispatch since fast DR needs to be predictable and reliable, and to achieve that through prices may be infeasible and through markets would require high transaction costs/complexity. Price signals and markets are more suitable for slow DR, which usually supports economic objectives and is not critical for system reliability and security.

Different DR program design options affect customers differently. Issues such as privacy, consumer risk, individual control, and perceptions of fairness affect user acceptance of residential DR programs. From a customer’s point of view, decentralized approaches without long-term contract obligations provide the highest assurance of privacy but also high risk. From a system operator’s point of view, these approaches result in unclear responsibilities in cases of contingencies. Engineering and economic mechanisms can deal with some customer issues, but customers also need mechanisms to deal with issues such as risk so that they will be willing to participate. These additional mechanisms make markets more complete and provide incentives for active participation.

Finally, better models are needed to understand the real effects of DR on power systems and markets. While small DR programs are unlikely to have large effects on system prices and system operation, large ones may. This means that most pilot studies today, which are relatively small, do not give us the full picture for all of the benefits and drawbacks to the various approaches. Therefore, we need large-scale system models that include engineering-economic interactions.

V. CONCLUSIONS

This paper investigated options for harnessing residential loads for DR. Economists and engineers often disagree on the best residential DR program designs likely because they view DR differently. Economists focus on the market benefits while engineers focus on the reliability and security benefits. To understand the engineering and economic arguments for and against various DR program designs, we analyzed three specific DR program design examples. Our goal was, in part, to understand which types of residential DR programs are best suited to which applications. However, our broader aim was to bring together engineering and economic perspectives on residential DR program design in order to achieve some common understanding.

Our analysis provides insights into the tradeoffs between market efficiency, customer choice, and system reliability. We find that reliability provision via fast DR may require dispatch since fast DR needs to be predictable and reliable, and to achieve that through prices may be infeasible and through markets would require high transaction costs/complexity. Price signals and markets are more suitable for slow DR, which usually supports economic objectives and is not critical for system reliability and security. Our hope is that this discussion can help DR researchers and practitioners from all fields reach some consensus on residential DR program design and deployment.

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REFERENCES

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<th>Example 1: Prices</th>
<th>Engineering pro</th>
<th>Economic pro</th>
<th>Engineering con</th>
<th>Economic con</th>
</tr>
</thead>
<tbody>
<tr>
<td>Individual modeling, control &amp; optimization</td>
<td>Customer optimizes own consumption/investments</td>
<td>No baselines</td>
<td>No privacy issues</td>
<td>Uncertain consumer behavior possible instabilities</td>
</tr>
<tr>
<td>Example 2: Dispatch</td>
<td>Predictable customer behavior controllability aggregate market bidding</td>
<td>Low risk to customer low risk to DR provider easy to implement</td>
<td>Aggregate modeling, control &amp; optimization baselines</td>
<td>True costs/benefits require mechanism design privacy issues contracts may not reflect system capabilities</td>
</tr>
<tr>
<td>Example 3: Markets</td>
<td>Individual modeling, control &amp; optimization</td>
<td>Customer optimizes own consumption/investments economically efficient</td>
<td>Individual market bidding</td>
<td>Market optimization via OPF non-tractable</td>
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