Innovation is rampant in the electric utility space, as stakeholders prepare responses to rapidly commercializing technologies like renewable energy and storage, and a significant need for reinvestment over the coming years. Responses include the changes to rates to incentivize customer behavior that reduces overall cost and required investment. Time of use rates are a popular example that have been around for decades, encouraging energy consumption when energy is cheap and discouraging consumption when it is expensive. These more sophisticated rates have traditionally been applied to large industrial and commercial users, and are now common for all rate-payers. Similarly, demand charges, which bill customers for their peak consumption, are prevalent (increasing? Decreasing?) for larger consumers. An electric grid must be built for the moment of peak usage, measured as the capacity of the network, and demand charges rest on the logic that consumers should therefore pay for their utilization of the system capacity. With the proliferation of smart meters and networked grids, there is also movement towards real-time pricing options, tying consumers behavior directly to the market costs incurred. The full range of rate structures is outside the scope of this paper (for further details see REFERNCE).

The common theme among these programs is providing consumers with price signals designed to incentivize specific behavior. By taking specific action at specific time, a consumer can reduce their energy cost; if they are in control of these actions, they can minimize the disruption caused by these actions. Two common forms of responding to these price signals are peak shaving and load shifting. Peak shaving seeks to minimize demand charges. Since demand charges are often based entirely on the consumer’s peak consumption in a month, the “demand event”, a reduction in load during this single instance will reduce the consumer’s bill, possibly significantly. Load shifting seeks to minimize energy charges by arbitraging energy across different time of use rates. Most often, this means consuming more at night when energy is cheap and less during the day when energy is expensive (‘shifting’ the load over the course of the day).

Both strategies require some action on the part of the consumer. This might mean changing behavior to shift load, such as changing the schedule of load-heavy industrial activities, like melting metal at night instead of during the day. Alternatively, it may be automated, for example with a smart air-conditioner that will switch off when it detects that load is approaching a ‘demand event’. Another option is to deploy an energy storage device; by timing the discharge or charge of a battery, a consumer can shave their peak or shift their load without requiring a change in behavior.

It is usually desirable to automate these responses, to reduce the burden on the consumer and reduce the risks of mistakes that eliminate possible savings. This is particularly the case for peak-shaving. The month’s bill is based on the single demand event; if no action is taken during this demand event, then this establishes the demand charge for the month, and the opportunity for peaking shaving that month lost. It should be noted here that successful mitigating response to a demand event will ‘move’ the moment of peak consumption to some another time in the month (the ‘alternative demand event’), but the alternative demand event is by definition lower than or equal to the original demand event; this is an inherent challenge to peak-shaving.

To frame this problem, all mechanisms by which the consumer can change their load, such as shifting production, turn on or off equipment, or deploy a battery, are considered dispatchable resources. The problem is therefore one of economic dispatch of these resources; this framing is suitable for peak-shaving and load-shifting strategies, but also for more complicated arrangements such as a economic dispatch of interchangeable resources in a microgrid (REFERENCE).

Next: How have people tried to solve this economic dispatch problem? How has reinforcement learning been applied to solve this economic dispatch problem?