Transactive Energy and Solarization: Assessing the Potential for Demand Curve Management and Cost Savings

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ABSTRACT

Utilities and local power providers throughout the world have recognized the advantages of the "smart grid" to encourage consumers to engage in greater energy efficiency. The digitalization of electricity and the consumer interface enables utilities to develop pricing arrangements that can smooth peak load. Time-varying price signals can enable devices associated with heating, air conditioning, and ventilation (HVAC) systems to communicate with market prices in order to more efficiently configure energy demand. Moreover, the shorter time intervals and greater collection of data can facilitate the integration of distributed renewable energy into the power grid. This study contributes to the understanding of time-varying pricing using a model that examines the extent to which transactive energy can reduce economic costs of an aggregated group of households with varying levels of distributed solar energy. It also considers the potential for transactive energy to smooth the demand curve.

CCS CONCEPTS

• **Computer systems organization** → **Embedded and cyber-physical systems**; • **General and reference** → *Design*; • **Computing methodologies** → **Model development and analysis**; • **Applied computing** → **Engineering**.

KEYWORDS

Transactive Energy, Community Choice Aggregation, Virtual Power Plant, Modeling and Simulation, Cyber-Physical Systems, Societal Implications

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1 INTRODUCTION

This study examines the interaction of transactive energy with distributed generation for a localized community of consumers who also produce some of their own electricity. In other words, it creates a virtual power plant (VPP) that is managed by pricing signals and adopts widely discussed parameters (variables), such as pricing techniques, battery presence, distributed energy resources (DERs), and load management through remote adjustment of appliances such as air conditioning units.

The key contributions of this study are twofold. First, it tests the effectiveness of pricing techniques to control load management. The findings of this paper can be directly applied in real life settings as it uses real energy consumption and weather data in Sacramento, California (CA). Second, by adopting several parameters, such as battery use, solar penetration rate, wattage of solar, and pre-cooling systems, this study attempts to produce the most effective transactive energy model that adopts solar energy. In this sense, the findings can lead to policy proposals that aid the development of transactive energy systems. It is especially applicable for regions where the solar penetration rate is high and increasing.

Transactive energy (TE) refers to *the combination of economic and control techniques to improve grid reliability and efficiency* [15]. One of the fundamental goals of TE is to coordinate the operation of new energy systems that contribute to the efficiency and reliability of the grid, which include many DERs. DERs refer to renewable energy generation technologies deployed in the distribution grid [13] at consumer's side and include local storage batteries, roof-top solar photovoltaic units, wind-generation units, and biomass generators. This study specifically focuses on the adoption of distributed solar energy and battery presence.

The study uses energy and pricing generation data from Sacramento, CA. In general, the state has government policies with relatively advanced use of time-of-use pricing and distributed energy generation. Customers in the state are served by public power companies for some cities (e.g., Sacramento, CA), rural electricity cooperatives, investor-owned utilities, and increasingly community-choice aggregation (CCA) organizations. The state does not have retail competition for customers, but CCAs in California have grown rapidly [12] [21]. Customer aggregation occurs when a local government or group of local governments enroll customers in their jurisdiction to purchase electricity for them as a collective unit. Doing so can provide customers with better prices. In California, some CCA organizations developed or launched in a form where the local government is involved in managing contracts and supporting energy efficiency and renewable energy generation, and the CCA organization begins to approximate a public power agency [20]. In these more advanced forms of CCAs, there is growing interest in VPPs. This research focuses on examining various DER configurations in VPPs.

Although the data and context are based on California, the analysis is relevant for other electricity utilities, cooperatives, and public power organizations in other states or countries that are considering the use of VPPs to enhance grid stability and efficiency. Any electricity provider that also wants to integrate higher levels of distributed renewable energy with pricing programs for demand management would find the analysis to be relevant. The study generates experiments to model the effects of TE on energy consumption decisions with varying levels of distributed renewable energy and examines the effects on household costs.

The central research question is: *what are the most efficient parameters in a decentralized energy system?* In answering this question, several relevant parameters are considered, such as pricing techniques, battery presence, the penetration rate of DERs, and load management and pricing optimization techniques such as precooling. The two pricing techniques tested were *time-of-use pricing* (TOU) and *real-time pricing* (RTP). In TOU, the price follows a set schedule, generally changing a few times throughout the day. In RTP, the price is varied over very short time intervals based on projected demand in those time frames. The experimental results show relationships between various combinations of these parameters and their effects on smoothing of the demand curve.

2 MOTIVATION

The use of DERs for energy generation has been increasing in California, which has the highest installed capacity of DERs in the United States with 3154 MW of DERs installed in 2014 [13]. However, despite their popularity, installation and maintenance cost is deterring many potential consumers from transitioning to DERs. A simulation model that indicates the economic savings of DER adoption and the most effective DER model could encourage more consumers to adopt DERs.

In addition, emerging TE technologies could smooth the demand curve and provide energy price systems that adhere to the supply and demand of energy at any given time [8] [17]. These benefits are expected to lead to more efficient grid management and cost savings. This study will help to clarify how different real-time pricing configurations interact with changes in the grid configurations, including DERs and energy storage.

By directly linking DER and TE and by using real-world data, this study builds on and complements experimental projects such as [11] [25] [14] by exploring a wider range of potential configurations of parameters than those are generally found in these projects.

Power grids equipped with TE are a highly complex CPS with additional human and economic factors that must be considered. A systematic approach to automate design of RTP models can lead to more adaptive load management as well as operational efficiencies.

3 RELATED WORK

3.1 Distributed Energy Resources

The role of distributed energy resources (DERs) has become increasingly important, particularly as the shift towards renewable energy becomes more prevalent. Concurrent with the growth of DER is the development of energy storage technologies, such as battery energy storage systems and flywheels [4].

DERs can be configured as microgrids and VPPs for enhancing their efficiency, cost effectiveness, and resilience [19]. In particular, VPPs are considered to be a cost-efficient integration of DERs [6]. This study contributes to the existing literature by examining various configurations of DER in a VPP setting that uses TE.

3.2 Transactive Energy

Transactive energy (TE) has been widely discussed in the literature, and it is considered as one of the key energy technologies that will result in more renewable and sustainable energy production and consumption. The advantages of TE are largely twofold: first, it allows for more predictive energy demand and consequently more efficient load management [9]. For example, [22] argued that buildings are 70 % of the load on today's grid, which makes the shape of electricity loads critically important in improving energy efficiency. TE can play an important role in smoothing the daily load. Second, for various reasons (more efficient load, integration of DER, etc.), transactive energy is also expected to dramatically reduce energy costs for both consumers and producers [9]. Transactive systems have been shown to reduce expected costs up to 75 % when local markets and flexibility are considered [18].

In this sense, real-time pricing (RTP) is one of the key characteristics of TE [8]. RTP requires constant data collection, often as frequent as every 5 minutes, which allows for more efficient peak demand and use of energy [27]. A 5 % reduction of peak demand can lead to $3 billion savings in the United States [10]. Furthermore, peak load reductions can lead to environmental benefits and a reduction of emissions. On the consumer side, there are economic benefits of RTP. Zethmayr and Kolata found that 97 % of regional customers would have saved money with RTP without changing their behavior because flat-rate supply service tends to incur higher bills than the hourly market price [27].

However, there are also challenges associated with RTP. One of the biggest challenges is privacy because there is a constant collection of energy consumption data. In order to solve the problem, there is ongoing innovation in privacy standards, guidelines, and regulation in various countries [16].

One of the most commonly used implementation methods for price modification is transactive incentive signals, in which the signal is sent by the utility to each consumer. Another commonly used implementation method is the transactive feedback signal, which is sent from the consumer to the utility and contains information regarding expected energy use. This has been modeled as time-of-use-based demand-response [24].

4 EXPERIMENT DESIGN

In order to simulate the community, their energy use, and the effect of different parameters, the system is modeled in a widely used open-source power-distribution system simulator known as GridLAB-D [7].

The simulation is based in Sacramento, CA, where DERs are widely prevalent and the region has sufficient weather variations to demonstrate dynamic feedback and control. The simulation models a community with 544 residential houses and 26 businesses using 2017 weather data, which was the latest and most reliable weather data for that area [3]. In order to optimize solar DER, a number of parameters are employed, such as solar panel power, solar panel penetration, the presence or absence of batteries, and pre-cooling. All simulations were run from 0:00:00 8/1/2017 to 0:00:00 8/15/2017. No heating was added to the model because it is unlikely that heating will be used in this area during the summer periods. Running the same simulation in the winter months likely would have resulted in solar panels and batteries used to store solar energy for later use and in having a reduced ability to flatten the load curve.

The above parameters were varied to observe their effects on the relevant outcomes: reducing utility demand, cutting costs for communities, reducing peak load on the system, and flattening the load curve. Each parameter combination was paired with both the TOU and RTP price schedules.

The functionality through which these outcomes could be improved is demand response. In other words, consumers will alter their energy demand based on changes in price. This is included in the model in the HVAC units. The behavior of these units is modeled by passive controllers in GridLAB-D, which, according to the procedure described in the following section, will decrease air conditioning use when prices are high.

4.1 Data Collection

Data were collected using government websites that published energy data, independent solar companies' websites, and other published data. Simulating a model requires assumptions on energy consumption, the choice of solar panels (i.e., efficiency of the solar panel), battery storage, and energy pricing scheme. Consequently, the following assumptions were made based on the data collected. Each household in California consumes approximately 546 kWh per month. This assumption is based on the 2018 data published by the U.S. Energy Information Administration [1]. This is the most recent dataset available for energy consumption per state, and there was little change in energy consumption in California from 2016 and 2018. Therefore, it is assumed that there is little change in energy consumption from 2018 to 2020.

Solar panels tend to vary in prices and efficiency. The five most popular solar panels in California (Solar Estimate 2020) were averaged, which makes the efficiency of the simulated solar panels 19.52 %. The average size of home solar installations in California in 2019 was 7 kW.

4.2 Experiment Parameters

Pricing technique: One of the key characteristics of TE is the adoption of different pricing techniques. This study adopts two different pricing techniques: time-of-use (TOU) and real-time pricing (RTP). TOU is one of the most widely used pricing techniques currently used in California. RTP is currently not deployed because of regulatory limitations regarding energy data collection, but it is the most commonly used pricing structure in TE [26]. Therefore, using an alternative platform such as simulation modeling is particularly useful in comparing these two pricing techniques. The two pricing systems are explained in detail in Section 5.

Wattage of the solar system: Simulations were executed with 5 kW solar panels, a common residential solar system generation capacity, and 7 kW, the most common generation capacity of residential installations in California.

Battery presence: The simulation also considers whether battery presence changes the efficiency of DERs. Batteries are considered particularly useful in many solar systems because they can provide energy after the sunset or even during days when direct sunlight is not available due to the weather restrictions. Each household is assumed to contain one battery storage system modeled on Tesla Powerwall, which includes a built-in inverter. However, the battery model can be configured for different capacities. One battery is assumed to be enough because it not only simplifies modeling, but, more importantly, it also removes the constraint of using two batteries at all houses, which could be cost prohibitive for some houses. Moreover, a single battery with configurable capacity makes the study more adaptable and flexible under different conditions and for different areas.

Solar penetration rate: The simulation introduces variation in the solar penetration rate of the community to analyze the extent to which solar adoption affects the demand curve, and consequently, grid management and reliability. Therefore, three different solar penetration rates are tested: 0 %, 25 %, and 50 %.

Pre-cooling: Without pre-cooling, the behavior of HVAC systems is determined only by the current price of power. With precooling enabled, HVAC systems will cool houses in advance of future power price increases, with the goal of saving money for consumers. Both conditions are tested.

5 SYSTEM ARCHITECTURE

In this section, we describe our approach to modeling the power grid and load, TOU and RTP pricing, and experiment automation.

5.1 Modeling the Grid and Load

The GridLAB-D model is based on the feeder model R1-12.47-2 [23] developed by Pacific Northwest National Laboratory (PNNL). The feeder model is comprised of a moderately populated suburban and sparsely populated rural area in which approximately 70 % of the circuit-feet are overhead and 30 % are underground. This feeder model was extended by adding triplex meters connecting existing triplex nodes to the houses. Triplex meters were also added to connect each solar panel and inverter pair to the grid (see Figure 1). In addition to power consumption from the HVAC, each residential house was connected to two ziploads: one using GridLAB-D's built-in *unresponsive_load* schedule, and the other using the built-in *responsive_load* schedule. The power use for the 26 commercial entities in the simulation was setup with unresponsive ziploads. Each business had loads modeling interior lighting, exterior lighting, plugs, gas waterheater, and occupancy.

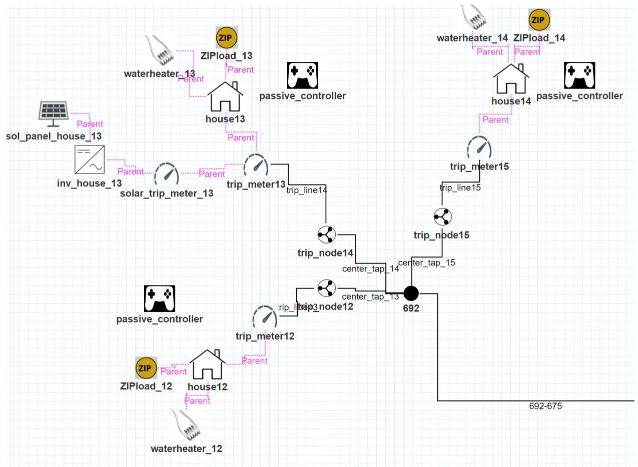

Figure 1: Part of the Grid Model used in Experiments

Consumer response to price changes is primarily modeled by a passive controller connected to each residential home's HVAC system. All HVAC's in our model were electric. These passive controllers respond to the price changes in the *stubauction* object (a basic GridLAB-D auction module), determined by the price schedule being used. The parameters *range_low* and *range_high* represent the most the consumer is willing for their house temperature to change due to transactive control. The range_low parameter was set as a random number in the range between -1 and -2, and range_high was set at a random number between 2 and 4. This means that the consumer with average preferences (76 °F base temperature) would be willing to have their HVAC vary the temperature between about 74 °F and 80 °F.

The stubauction object in GridLAB-D was used in conjunction with passive controllers, which responds to price changes. The stubauction period was 300 s, meaning that RTP price updates occur every 5 minutes.

Within the maximum range of temperature alterations, HVAC behavior is modeled by piece-wise functions [2] corresponding to customer willingness to change temperature within their maximum range. Variable *ramp_high* represents the temperature increase that would accompany a 1 standard deviation increase in price. Variable *ramp_low* represents the temperature decrease that a customer would be willing to pre-cool to in the case of a price 1 standard deviation below average. Both ramp_high and ramp_low are set to a random number between 1 and 4.

Group IDs were assigned to each triplex meter indicating whether it was residential, commercial or solar meter. Using these group IDs, collectors aggregate the data from each of residential, commercial, and solar entities to get a clear picture of energy production and consumption in each simulation. The default powerflow solver method in GridLAB-D, Forward Backward Sweep (FBS), was used for the simulation. The minimum timestep in GridLAB-D was set to 15 s, which was found to offer enough precision without resulting in prohibitively long simulation runtimes. Treatment of transient stability would require enforcing transient stability thresholds as invariants and relating transient stability with price variations, which is outside the scope of this paper.

The temperature inside the house can greatly affect the energy bill. The average cooling temperature in hot-dry states, which includes California, is 76.4 °F [5]. The cooling set points were randomized for each house using a uniform distribution within 2 °F of this average, between 74 °F to 78 °F. This specific range was chosen to give variation among different households, which would result in a more realistic data.

5.2 TOU & RTP Pricing

For TOU, data were used from Marin County, CA. During weekdays, the peak demand period is from 1 p.m. to 7 p.m. and park peak period is from 10 a.m. to 1 p.m. as well as 7 p.m. to 9 p.m. During weekends, the park peak period is from 5 p.m. to 8 p.m. All other hours are considered off-peak hours.

RTP price schedules are generated from the results of TOU simulations. Two strategies were employed to reduce peak power usage and flatten the demand curve: raising prices during times of high usage and lowering prices in advance of high usage periods, both based on the TOU simulation results. Two *lookahead periods* were used in which the demand over the next set of time-frames would be averaged together. In the first, shorter lookahead period, higher demand in the TOU simulation corresponds to proportionally higher price for the RTP price schedule. In the second, longer lookahead period, higher demand in the TOU simulation would correspond to a proportionally lower price for the RTP price schedule. These two candidate price schedules are averaged together according to a weighting.

Based on the TOU simulation results, let U_p be the mean power usage in the previous *'x'* time-slots of 5 minutes each, and U_n be the mean power usage in the next *'y'* time-slots of 5 minutes each, A be the average power usage for the entire simulation, and *w1* and *w2* be the weighting of the *'x'* and *'y'* lookahead periods respectively (where, $w1 + w2 = 1$), then

$$P_+ = U_p/A * avg\_price \tag{1}$$

$$P_- = (2 - A/U_n) * avg\_price \tag{2}$$

$$P_f = P_+ * w1 + P_- * w2 \tag{3}$$

After setting up TOU and RTP capabilities, parameters x, y, and *w1* (as $w2 = 1 - w1$) were varied to determine the best combination for an RTP price schedule. The process of generating price schedules, running the GridLAB-D simulation, and processing the results of the simulation were automated with a bash script. After each simulation run, results such as residential load, commercial load, and solar load were reported every 5 minutes. From these results, a Python script automatically calculated metrics such as the peak power demand, the standard deviation of power demand, and a statistic we created: a 6-hours $MaxMin_d$. In $MaxMin_d$ metric, the average of 5 minimum load time-frames was subtracted from the average of 5 maximum load time-frames over each 6-hours time-period of the simulation. This metric aimed to show which simulation parameters resulted in large variation over short time-frames, even if the absolute peak load over the simulation wasn't extremely high.

Name	Max (VA)	SD (VA)	$MaxMin_d(VA)$	Res Bill ($)	Sol Bill ($)
7_batt_RTP_50	2070750	306491	2113857	65.09	-62.94
7_batt_RTP_50_nopre	2179040	324463	2142096	64.18	-61.71
5_batt_RTP_50	2464840	358899	2389285	74.73	-15.67
5_batt_RTP_50_nopre	2501670	377959	2403859	73.96	-14.88
7_batt_RTP_25	2469690	425150	2653535	82.51	22.98
7_batt_RTP_25_nopre	2460750	438485	2658196	82.15	22.94
5_batt_RTP_25	2766350	457178	2834549	87.24	45.01
5_batt_RTP_25_nopre	2700960	470534	2872458	86.98	44.77
5_nobatt_RTP_50	2538620	419921	3036072	74.75	-7.45
7_batt_TOU_50	3188990	348845	3210814	69.55	-81.64
7_batt_TOU_50_nopre	3185220	347426	3219136	69.35	-81.84
7_nobatt_RTP_50	2485180	436913	3340449	65.55	-44.11
0_batt_RTP_50	2860000	560933	3399355	99.30	99.30
0_batt_RTP_25	2816270	562452	3416696	98.86	98.86
0_nobatt_RTP_50	2901270	559742	3436602	99.06	99.06
0_batt_RTP_50_nopre	2883640	577873	3508441	98.43	98.43
0_batt_RTP_25_nopre	2986200	578469	3538669	98.76	98.76
5_batt_TOU_50	3550930	403705	3638344	80.60	-27.39
5_batt_TOU_50_nopre	3527530	404007	3671989	80.47	-27.52
7_batt_TOU_25	3461310	467367	4025024	89.99	18.35
7_batt_TOU_25_nopre	3453180	468556	4061837	89.80	18.16
5_batt_TOU_25	3591500	499584	4356122	95.25	44.08
5_batt_TOU_25_nopre	3621350	500911	4377977	95.13	43.96
7_nobatt_TOU_25	3626040	500120	4480413	90.68	19.04
5_nobatt_TOU_50	3619740	481036	4493945	81.75	-26.24
5_nobatt_TOU_25	3642000	522936	4561583	95.79	44.62
7_nobatt_TOU_50	3656030	496599	4816567	70.99	-80.20
0_batt_TOU_50	3637330	611532	5055585	107.96	107.96
0_nobatt_TOU_50	3659540	609829	5064896	108.57	108.57
0_nobatt_TOU_25	3640000	609522	5070649	108.50	108.50
0_batt_TOU_25	3649990	610658	5081957	108.31	108.31
0_batt_TOU_25_nopre	3652230	611289	5098970	107.96	107.96
0_batt_TOU_50_nopre	3645750	613297	5128058	107.84	107.84

Table 1. Simulation Results

The values of x = 6 time-slots (30 minutes), y = 115 time-slots (575 minutes), $w1$ = 0.1, and $w2$ = 0.9 were found to minimize peak load, standard deviation, and 6-hours $MaxMin_d$.

5.3 Experiment Automation

In order to run large numbers of experiments efficiently, the process of running GridLAB-D simulations was automated using a bash script (see Figure 2). The simulations are run by entering the following line (or a variation) in git bash:

sh runGLD.sh panel_power battery <.GLM file> x y w1

Here, *panel_power* is an integer representing the power in kW of the solar panels; *battery* specifies running a simulation with 13.5 kW batteries, while the alternative *nobattery* specifies running a simulation with no batteries present.

First, the bash script edits the price schedule generation Python script using the desired parameters: *x*, *y*, and *w1*. The price schedule generation script then executes, using these parameters and a previous TOU simulation to generate the new price schedule. Next the bash script edits the GridLAB-D model file according to the specified parameters. After the simulation, the bash script generates the bills for residential customers with solar panels, residential customers without solar panels, and commercial entities, as well as calculating descriptive statistics of the power load graph.

6 EXPERIMENT RESULTS

Table 1 shows a subset of the simulations run along with some evaluation metrics. The name of the simulation is comprised of the following parameters in order:

- Power generation capacity of the solar panels (0 kWh, 5 kWh, or 7 kWh);
- *batt* if the simulations have batteries present, otherwise *nobatt*;
- *RTP* if real-time pricing was used, and *TOU* if time of use pricing was used;
- The percentage of residential houses that have solar panels (25% or 50%); and
- *nopre* if precooling was disabled for that simulation.

The column names in the simulation results, from left to right, shows: name of the simulation (*Name*); grid power load (*Max*); the standard deviation of grid power (*SD*); the differences between maximum and minimum ($MaxMin_d$ – defined in Section 5); the power bill for residential customers without solar panels for the 2 weeks simulation (*ResBill*); and the power bill for residential customers with solar panels for the 2 weeks simulation (*SolBill*).

6.1 Effects of Parameters on Power Costs

There were three main effects of the parameters on power costs:

(1) **RTP vs TOU pricing**: The RTP model used for this study does not seem to drastically reduce prices for consumers. We observed that in each RTP vs TOU simulation pair in which the other variables were held constant, RTP slightly reduces the energy bill for residents without solar panels, and increases the energy bill for residents with solar panels. One potential reason for this could be shifting of slightly higher prices to price responsive customers.

(2) **Battery storage**: Batteries are found to have little effect on the energy bill of residents without solar panels, but reduce the bill for residents with solar panels. A potential reason for this could be that for customers without solar panels, battery could serve to store power during lower prices, which could later be used when prices rise. On the other hand, for customers with solar panels, the effect of local storage might be negated by the higher prices they could get by pushing excess power in the grid during that time.

(3) **Solar panel penetration and generation capacity**: Higher solar panel penetration and higher solar panel power generation capacity both correspond with significant reductions in the energy bill for both categories of customers due to overall reduction in power demand from utilities.

6.2 Effects of Parameters on the Duck Curve

There were also significant impact of the parameters on the *duck curve* (a graph of grid power load that dips in the middle of the day during solar power generation and then rises at the end of the day as people use more power in the evenings) as follows:

(1) **RTP vs TOU pricing**: RTP significantly smoothed the duck curve when compared to TOU by shifting load before peak usage (see Figure 3). RTP simulations have lower *max* power, standard deviation (*SD*), and $MaxMin_d$ than TOU simulations when other variables are kept constant. In fact, TOU simulations with transactive control, had more undesirable duck curves than without TE, potentially due to abrupt changes in power demand when price changes.

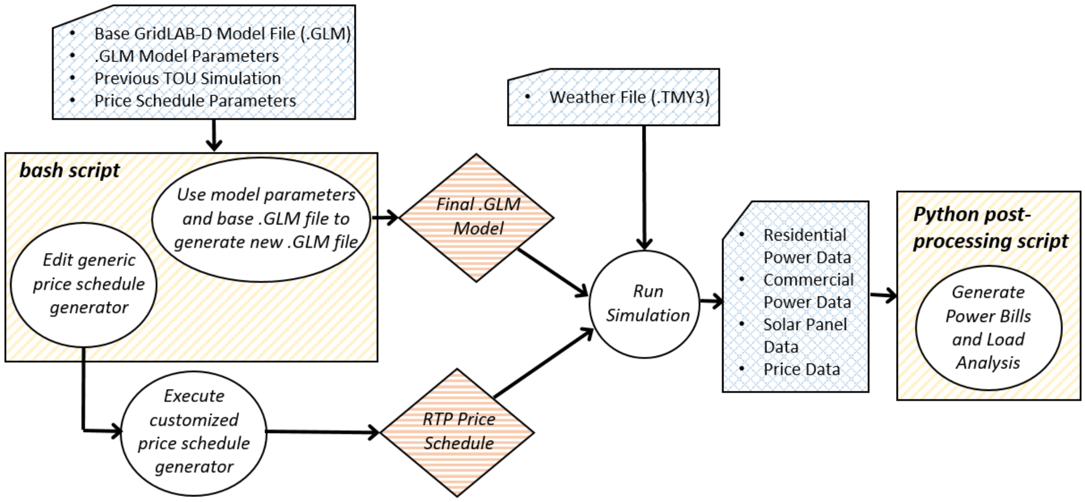

Figure 2: Simulation Automation Workflow

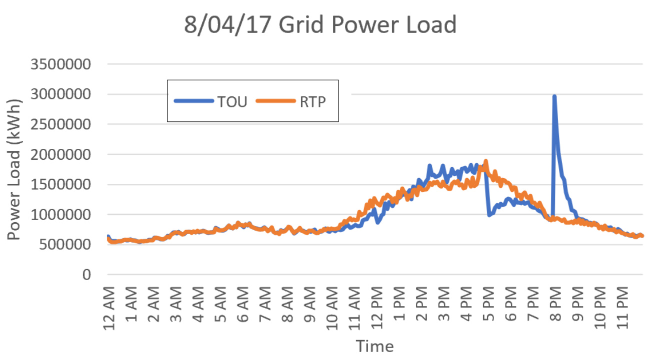

Figure 3: TOU vs RTP Comparison

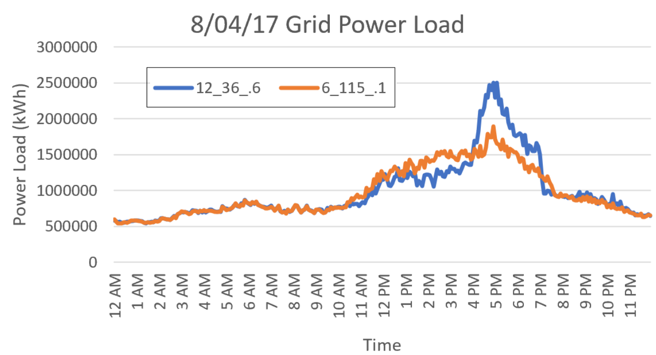

Figure 5: Effect of Tuning RTP Parameters

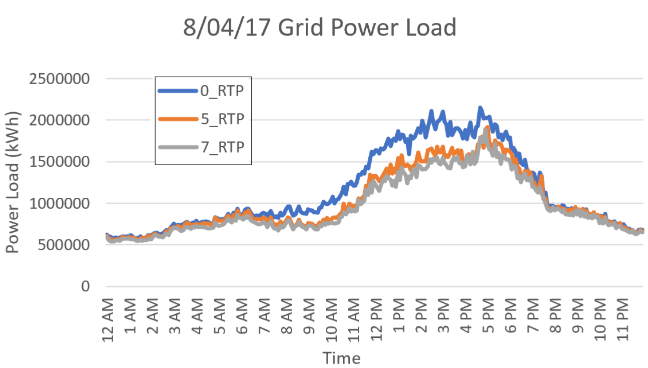

Figure 4: Solar Panel Power Comparison

(2) **Battery storage**: Batteries also have a significant impact on smoothing the duck curve for much of the same reasons that they reduce costs for residents with solar panels. Houses with batteries will use less grid power during peak hours due to the raised prices during those time-frames.

(3) **Precooling**: The results show that precooling has a minor smoothing effect. Each RTP simulation with precooling has a slightly lower standard deviation and $MaxMin_d$ difference than the same simulation without precooling, but the duck curves are not significantly different.

(4) **Solar panel generation capacity**: Higher power generation capacity of the solar panels reduced grid power demand, as shown in Figure 4, especially during the middle of the day when most of the solar power is produced. Increasing the number of solar panels (50% as opposed to 25%) has a very similar effect on the duck curve as increasing the power generation capacity of the solar panels.

6.3 Effect of Tuning Price Schedules

Through tuning the parameters of the RTP price generator, it was possible to smooth the duck curve significantly. Figure 5 shows a comparison between an RTP simulation with the initial guess for parameters (12_36_.6: x = 12; y =36; and w1 = 0.6) and the set of parameters selected after testing (6_115_.1: x = 6; y = 115; and w1 = 0.1) as described earlier in equations (1), (2), and (3).

7 CONCLUSIONS & FUTURE WORK

The study demonstrates the benefits of transactive energy with real-time pricing in the context of a local electricity network with distributed solar energy and virtual power plant. The systematic approach to designing RTP pricing shows how the daily demand curve can be made smoother under specifiable conditions. However, the effect on customer prices varies with respect to the use of solar panels, and more research is needed to understand how customers can benefit from the arrangement. The study examined diverse configurations, but many more are possible, and future research could examine additional effects on the two goals of a smoother demand curve and customer pricing benefits.

Further research could also improve upon RTP effects demonstrated by this paper by tuning the price schedule parameters for each simulation. More specific RTP parameters for each model could smooth the duck curve even better than shown in the presented results. With respect to policy implications, the study indicates that utilities and regulators should continue to engage in both simulation experiments and real-world experiments to understand better the effects of transactive energy with real-time pricing. These experiments should include conditions that continue to explore the combinations of battery storage, levels of solar power generation capacity and penetration, and pricing strategy.

8 ACKNOWLEDGMENTS

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