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Abstract

Dynamic price signals are now being tested as a method to incentivize customer distributed energy resources (DER) flexibility to support distribution system and bulk grid needs. Use of DER flexibility includes load shifting and management of storage resources in response to forward market prices and real-time 5-minute prices. The work presented here compares the impact on voltage of two price-responsive heat pump controllers. The first controller implements rule-based real-time control based on 5-minute real-time prices. The second controller uses a building-model-based approach to optimize load using day-ahead hourly prices. These approaches are evaluated using GridLAB-D simulations.

Simulation results show both controllers adjusting temperature setpoints in response to price movement. Larger price movements result in larger instantaneous changes in temperature setpoints with heat pumps turning on or off together, thus inducing significant power flow volatility. The average substation power flow change for the real-time controller, time step-to-time step, was approximately 10 % of the peak load. Some observed power flow changes were equivalent to dropping 75 % of the load on the grid in response to a single price jump. The power flow volatility resulted in voltage volatility at customer meters with average voltage changes, time step-to-time step, of 2.3 V (19 % of Range A voltage limits).

Analysis suggests that power flow volatility may be expected when many devices are price-responsive and controllers have the goal of reducing cost without considering voltage. A real-time market price signal may not be suitable for congested grids, especially as the percentage of price-responsive load increases, since the volatility of the price signal creates voltage volatility. In addition, the price signal, rising and falling multiple times per hour, induces synchronization of heat pumps which increases the magnitude of power flow and voltage changes. Care must be taken to reduce the volatility of the price signal and boost hosting capacity to support synchronized price response by a large percentage of load.

Keywords

distribution grid; dynamic pricing; GridLAB-D; hosting capacity; power quality; volatility.

Abbreviations

DAP	Day-ahead market price
DER	Distributed energy resources
LFC	NIST load-forecasting controller
RTC	PNNL real-time controller
RTP	Real-time market price
RTP_{avg}	Hourly-averaged RTP

1. Introduction

The electric grid is undergoing significant changes due to the proliferation of distributed energy resources (DER) and accompanying load growth, which can strain existing distribution grids. Carefully considered tariffs can provide input to automated controls to help manage both capacity challenges and voltage control on the distribution grid.

Buildings represent 74 % of electrical load in the U.S. [1], but buildings also contain storage (both thermal and electrical) and generation, and these can all offer flexibility for grid services such as voltage regulation and frequency response. Heating, ventilation, and air conditioning (HVAC), and water heating are significant sources of electricity consumption in buildings, while battery charging for vehicles and stationary applications is growing. Intelligent controls can manage these loads to provide flexibility to the grid and support the integration of intermittent renewable generation.

Flexibility is the capability of DER, including generation, storage, and loads, to adjust a building's demand profile across different timescales in response to grid needs [2, 3]. Grid needs are communicated by demand response (DR) event signals, market signals, or automatic sensing (e.g., voltage and frequency). In response to providing grid services, customers may receive payments or other incentives via a market or DR program.

Dynamic prices, defined as hourly or shorter time interval prices based on energy market clearing prices, can communicate energy supply conditions to flexible devices on the distribution grid. Dynamic price tariffs are effective for incentivizing both manual and automated responses [4]. Two wholesale market clearing prices are used in practice now: the real time market 5 min price (RTP) and the day-ahead market hourly price (DAP). The number of RTP tariffs is small but growing in use [5, 6]. The experiments reported here compare the impact of these two different dynamic price tariffs on distribution grid power quality. The first tariff distributes the clearing price of the wholesale real-time market as a 5-minute price signal, and the price for each time interval is received just minutes prior to the interval start time. The second tariff distributes the clearing price from the wholesale day-ahead market as hourly prices received day-ahead. These approaches are compared to a constant-temperature baseline with flat-price tariff (no load response to price).

The DAP provides an indication of tomorrow's electricity prices. The RTP represents the marginal price of generation to the bulk system at different transmission system nodes and is more volatile than the DAP. Typically, 95 % of energy transactions in the wholesale energy markets are scheduled in the day-ahead market, with the rest scheduled in real-time [7].[1]

While wholesale RTP provides a signal for incentivizing real-time demand adjustment to support the electric grid and can save money for customers who react quickly, it also has some weaknesses. A real-time signal is not useful for planning purposes, except by reference to its historical behavior. The real-time market is responding to minute-to-minute imbalances in supply and demand and therefore the RTP can change in unpredictable ways. In the context of distribution system flexibility, RTP induces DER to adjust power consumption. When price increases, controllers are likely to reduce load and the feeder aggregate power flow will drop in

[1] Not all energy purchased by wholesale customers is procured through the short-term energy markets; a large percentage may be purchased via long-term bilateral contracts and many utilities own a significant percentage of their own generation resources.

proportion to the price increase[2]. Wholesale RTP is a marginal price indicating bulk grid supply needs; it is not intended to have a connection to local voltage levels. However, aggregate response of loads to RTP can induce local voltage changes.

DER management based on next-day hourly prices can enable optimization of load across the next day, balancing cost and comfort. Unlike the response to RTP, DAP provides no signal to flexible DER to respond to real-time grid supply needs, or to over-supply from renewable generation. Nonetheless, next-day prices are more stable, and energy purchased day-ahead may benefit resource planning both for the building owner and for the grid operator. One approach that has been tested in a utility pilot utilizes day-ahead commitments based on DAP combined with RTP for real-time adjustments [8, 9]. This has the effect of a day-ahead retail market that brings customer demand flexibility into the wholesale market cycle, resulting in wholesale clearing prices that consider demand flexibility. It also limits customer exposure to volatile real-time prices.

In this research, two different control approaches manage heat pump power consumption using these two price signals. The goal of each is to minimize customer energy cost by adjusting house temperatures within allowed occupant limits. The two controllers work in fundamentally different ways. The first approach responds to the RTP signal and enables fast response to real-time grid needs. The second approach responds to the DAP signal to enable effective load planning.

A number of research reports in recent years have focused on DER-related voltage challenges [10–13], specifically tied to PV systems. PV over-generation may result in backflow to the substation as well as elevated voltage levels. After the sun sets, heavy demand and/or localized large loads (e.g., from EV charging) may result in under-voltage conditions. In this study, the high penetration of PV systems does result in over-voltage conditions at certain times and locations, while peak load produces undervoltage conditions in a few locations on the distribution feeder studied.

Some studies have looked specifically at the use of flexible resources for voltage management [13, 14, 15]. They demonstrate the effectiveness of batteries and loads for energy provision and inverters for reactive power provision to manage PV generation-induced voltage swings, thereby increasing hosting capacity. However, these studies do not address the impact of dynamic prices on voltage. A review paper [16] on transactive energy markets identified the need for research on how to account for congestion (i.e., voltage control) in market clearing prices.

This research demonstrates the impact price volatility can have on voltage variability due to rapid shifts in power flows when heat pump controllers react to fluctuating prices. The algorithms described in Section 2.2 were neither constrained by the grid conditions nor optimized to consider voltage stability. This study highlights the impact of controllers sensitive only to price that could lead to creating an undesired emergent voltage variability.

[2] Controller and device heterogeneity will help to minimize this effect, but if every controller has as a goal to reduce cost with reference to the same volatile price signal, then power flow volatility will result.

2. Materials and Methods

2.1. Grid modeling

In this study, we used the U.S. National Institute of Standards and Technology (NIST) co-simulation tool called the Universal Cyber-Physical Systems Environment for Federation (UCEF) [17]. Key simulation components (federates) consist of the GridLAB-D grid solver working with a grid model, along with two different heat pump controllers operating based on market prices. GridLAB-D provides quasi-steady state distribution power flow solutions along with simultaneous house and market model solutions.

The grid model is a large feeder based on the IEEE 8500 reference grid (hereafter called "8500 grid") [18], Fig. 1. It is a residential feeder model populated with 1977 single family homes, each with controllable air conditioning systems (air-source heat pumps) and uncontrolled plug loads. For these homes, 90 % have PV systems and 50 % have electric resistance water heaters. Additionally, house thermal properties and sizes of components (PV systems, heat pumps, water heaters) are varied randomly across a wide range of house sizes and age characteristics, representative of existing house stock. Occupant comfort parameters are also varied across a range from those who want to save money to those who want more comfort. This diversity influences strength of reaction to changing electricity price. Load operation schedules are also randomly varied. More detail is provided in [19].

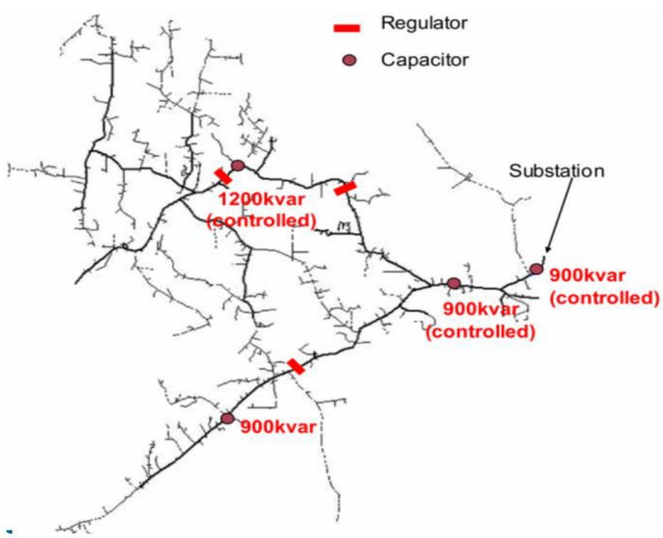

Fig. 1 IEEE 8500 reference grid [18] schematic.

2.2. Heat Pump Transactive Controllers

The experiment made use of two separate controllers: the PNNL Real-Time Controller (RTC), and the NIST Load Forecasting Controller (LFC).

The RTC uses rule-based control, adjusting indoor setpoint temperatures at every 5-min interval, moved up or down in proportion to the changes in RTP. The thermostat controller calculates the cooling setpoint temperatures (T_{csp}) (summer) for each house as:

$$T_{csp} = T_{set} + \frac{2 \cdot offset\_limit}{k \cdot \sigma}\left(price - P_{avg}\right), \tag{1}$$

where

T_{set} = desired indoor air temperature (°C),
$offset\_limit$ = extent that adjusted setpoint can move above or below T_{set} (°C),
k = responsiveness desired by the consumer (unitless),
σ = standard deviation of the price over the last 24 hours ($/kWh),
$price$ = real-time price ($/kWh), and
P_{avg} = average price over the last 24 hours ($/kWh).

T_{csp} values are sent to the GridLAB-D model every 5 min to update the house temperature control setpoints for each house. Equation 1 shows that setpoint temperature for each house increases linearly with price, and the slope of the increase is proportional to the *offset_limit* and inversely to comfort parameter, k, and price standard deviation. That is, a customer with higher comfort parameter will see less temperature increase, and likewise there will be less temperature increase when the range of prices (standard deviation) increases.

The NIST LFC, Fig. 2, runs once per day to generate next-day house setpoint temperatures using day-ahead market prices.

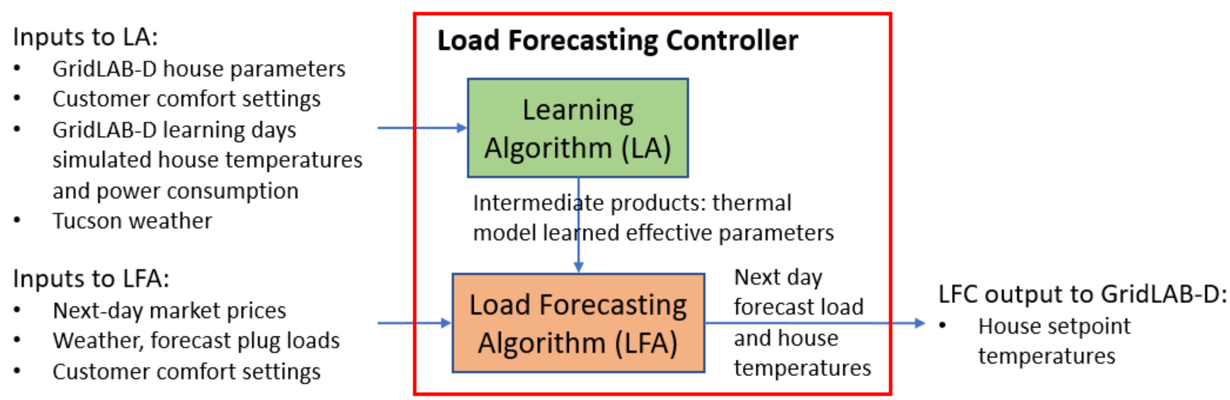

Fig. 2 Schematic representation of Load Forecasting Controller with information inputs, intermediate products, and outputs to GridLAB-D.

The LFC is comprised of two main components, a Learning Algorithm (LA) and a Load Forecasting Algorithm (LFA) [20]. The LA [20, 21] uses parameter optimization to learn key thermal parameters of a first-order lumped capacitance model (LCM) from historical measured or simulated data for each house. It optimizes these thermal parameters by minimizing the error between simulated or measured indoor temperature and the output of the LCM. The LCM forecasts the indoor temperatures from estimates of heat pump power, solar heat gain, heat gain from plug-loads, and outdoor air temperature. GridLAB-D simulations of three preceding days provide training data for the LA.

The objective function of the LFA is formulated to minimize cost while maintaining thermal comfort. The LFA predicts the hourly energy consumption of each residential house using the LCM with LA properties tuned to each house. Customers' thermal comfort requirements are expressed using a comfort parameter analogous to that used in the RTC approach. Weather conditions were obtained from historical data for Tucson Arizona. A forecast of plug-loads was obtained from simulation of the 8500 grid in GridLAB-D. The LFA uses a multi-objective optimization model [20] to find an optimal heat pump schedule that balances cost and comfort. The resulting LCM indoor temperature is used as the cooling setpoint temperature sent to GridLAB-D. More details on the LFC thermal model and optimization algorithms are provided in [20].

GridLAB-D has its own more detailed model of a house. At each simulation step, GridLAB-D solves power flows in the grid with the house load as a key component. The resulting house loads are not identical to LFA estimates, but similar [19].

2.3. Experiment Design

The UCEF co-simulation environment was used to simulate grid operations and house performance for July 6 and July 7, 2017. The experiment used California Independent System Operator (CAISO) RTP at the Tucson, AZ node. To enable comparison of energy use paid for based on RTP vs. DAP (where DAP was much lower than RTP on July 7), the decision was made to use the average hourly RTP (RTP_{avg}) in place of DAP for these simulations. These two price streams are shown in Fig. 3 for the test days.

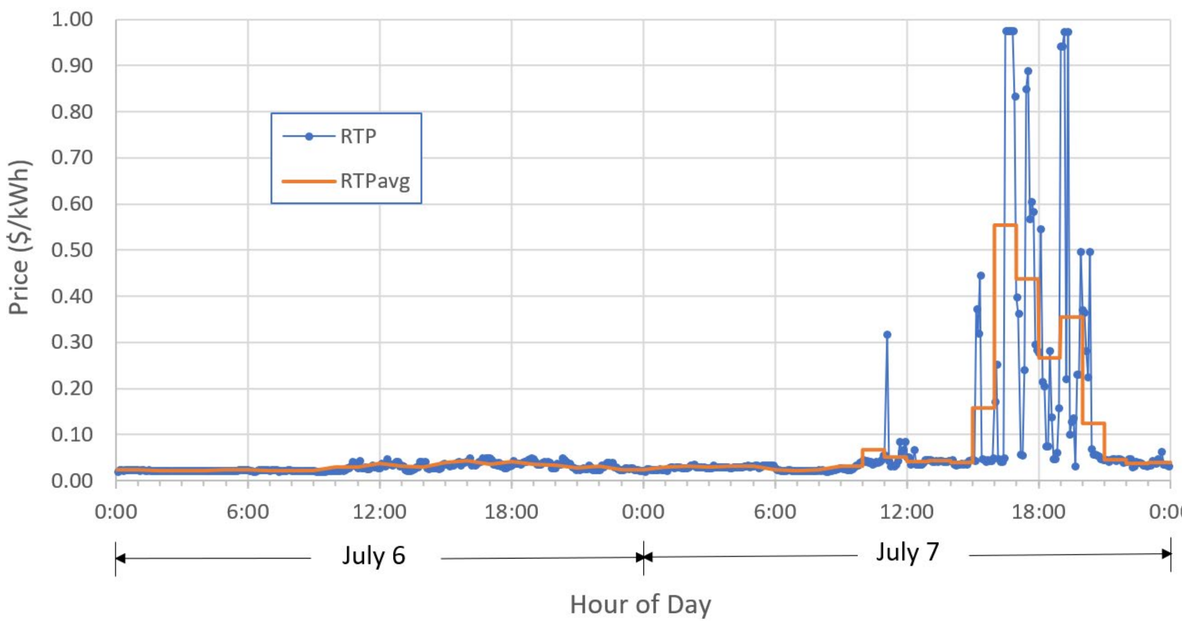

Fig. 3 RTP and averaged hourly RTP (RTP_{avg}) for July 6 and 7.

Fig. **3** shows a highly volatile RTP on July 7, with price spikes from 3 p.m. until 8 p.m. July 6 has no RTP price spikes, and in fact, the RTP was lower than the CAISO DAP. Typical days in the preceding 2 weeks saw a few RTP spikes. Additionally, there is still significant volatility in the RTP signal on July 6 (as will be seen below), but that volatility only covers a range of several cents.

For this study, GridLAB-D simulations ran one day at a time using a 1 min time step. LFC and RTC temperature controllers provided adjusted setpoint temperatures on a 5 min schedule to follow the 5 min real-time market signal. Tucson outdoor temperature and solar irradiance data were provided to the grid simulator at 5-min resolution.

3. Results

This simulation work examined customer comfort, cost, and distribution grid impacts for the two different heat pump controllers operating on RTP vs. day ahead (RTP_{avg}) price signals. The thermal and economic results are presented in more detail in [19] while this paper focuses on distribution voltage impacts of the price-responsive heat pump controllers. The two controllers manage energy use by adjusting the house indoor temperature setpoints in response to prices. The two controllers operate on different price signals using different approaches (day-ahead thermal energy storage planning vs. real-time reaction) leading to very different indoor temperature setpoints. It is valuable to look at some of the setpoint values for July 6 and 7 to understand the impact on distribution grid power flows and voltage.

3.1. RTC and LFC Temperature Adjustment

The RTC and LFC controllers produce different temperature setpoints in an effort to manage heat pump operation costs while maintaining comfort. The temperature setpoints for an example house (one with a customer having a tolerance for more temperature adjustment to save money) are shown in Fig. 4 for July 7, along with the RTP profile on the secondary axis. The RTC algorithm raises T_{csp} in the morning due to the already high (compared to July 6 average) morning prices. RTC has no foresight to expect even higher prices in the afternoon. The LFC, on the other hand, has no reference to July 6 prices and is seen here performing pre-cooling (from 8:00 a.m. to 9:30 a.m. and 12:00 p.m. to 3:00 p.m.) in anticipation of even higher afternoon prices. LFC attempts to reduce cost by letting the indoor temperature float during the peak price periods. The LFC does not see the RTP volatility and does not react to it. The RTC setpoint follows the RTP signal up and down (per Eqn. 1) with higher volatility compared to the LFC temperature setpoint. Note that T_{csp} has a customer comfort limit at T_{max} that controls how high the indoor temperature can be set.

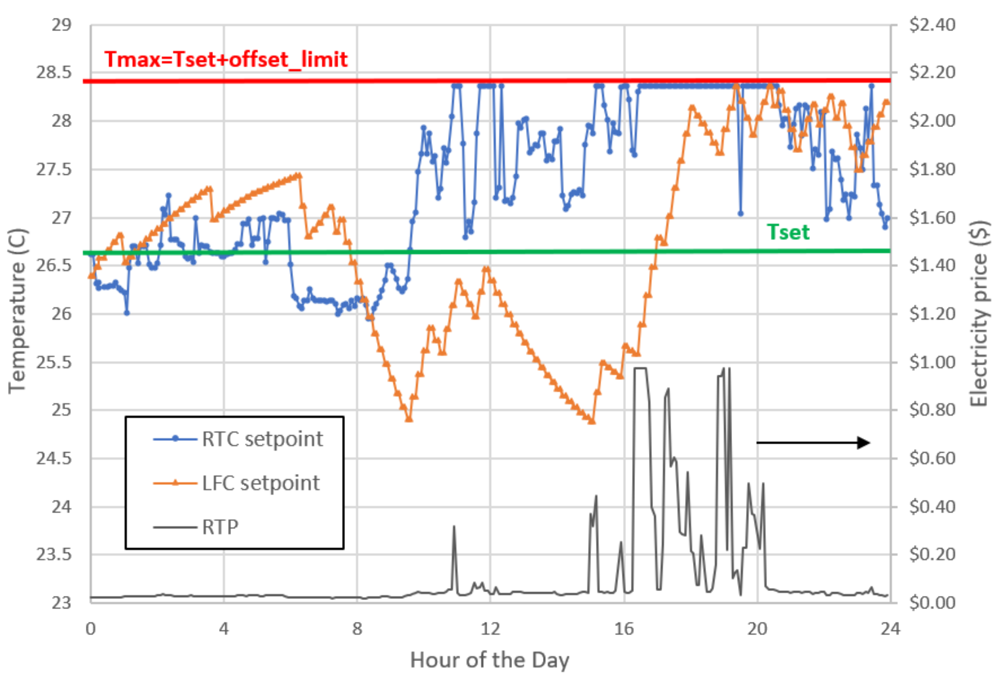

Fig. 4 Cooling setpoint temperatures from RTC and LFC controllers for a low-comfort house, July 7, 8500 grid. The RTP profile is shown at the bottom.

On July 6, the RTP price peak and volatility is lower compared to July 7. Fig. **5** presents the July 6 RTC and LFC temperature setpoints for the same house seen in Fig. 4. RTC T_{csp} follows the rise and fall of the RTP. The LFC allows the T_{csp} to drift up toward T_{max} during the highest price periods. Examination of the voltage and power flow fluctuations in Section 3.2 will show that the July 6 prices still induced synchronized temperature adjustments resulting in strong power flow fluctuations comparable to those seen in the July 7 data.

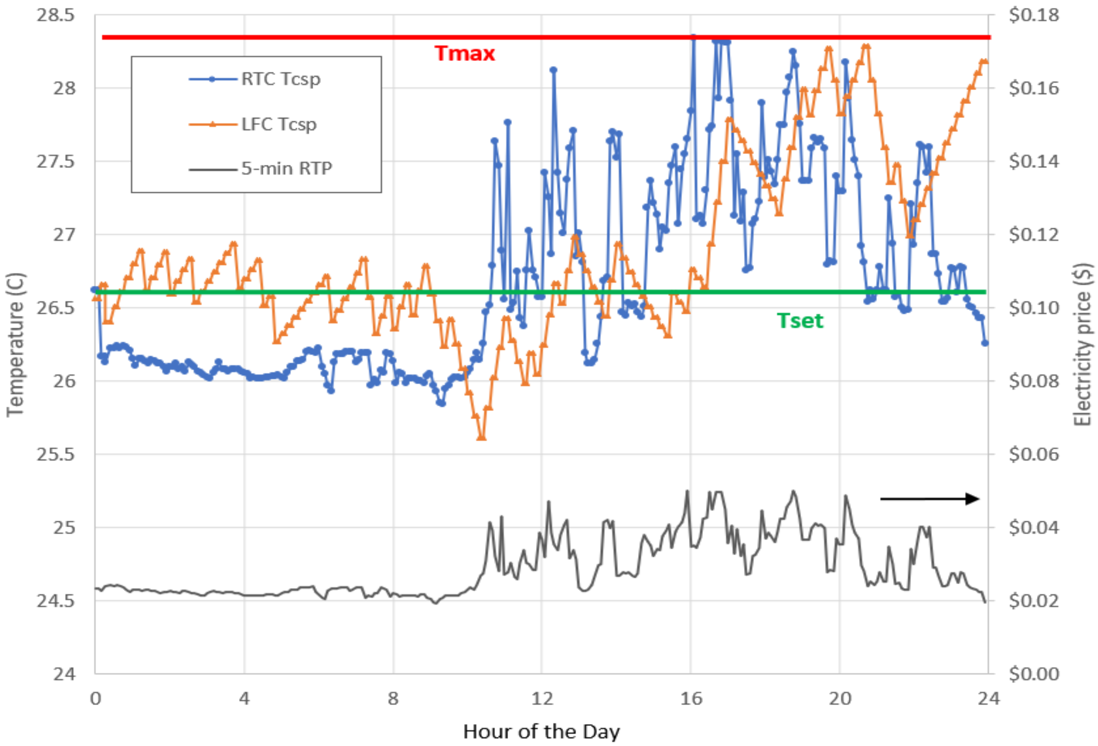

Fig. 5 Cooling setpoint temperatures for RTC and LFC, July 6. Compare to July 7 data for the same low-comfort house in Fig. 4.

3.2. 8500 Grid Power and Voltage Dynamics

GridLAB-D simulations provided minutely results for substation power flows, house meter voltages, as well as voltage regulator and capacitor bank actions. Results suggest that the RTC and LFC controllers can have significantly different impact on the distribution power quality and hardware action.

3.2.1. Voltage Variability

The normal acceptable voltage range for service below 600 V as defined by ANSI C84.1 [22] is nominal voltage +/- 5 %, or a service voltage of 114 V up to 126 V. This is termed Range A, and the duration of time outside this range is a measure of distribution grid power quality and can be used to judge the impact of the control algorithms. The GridLAB-D PV inverter model does not control on voltage and allows PV generation at voltages above 126 V.

The number of PV systems on the 8500 grid used in this experiment is above what a utility would normally permit, given that overvoltage conditions are present when the sun is shining. The simulation results in Table 1 show the presence of voltage violations. In the case of the baseline simulations, voltage violations can be attributed to over-voltage conditions that are almost entirely limited to the morning when there is significant solar generation while the heat pump load is still low.

In contrast, the over-voltage counts for LFC and RTC occur throughout the day and are primarily tied to price changes. The LFC and RTC controllers adjust T_{csp} in response to prices, leading to synchronized power flow changes and voltage fluctuations. In the case of RTC, T_{csp} is changed in proportion to RTP every 5 min. In the case of LFC, each house is separately optimized based on hourly day-ahead RTP_{avg} but temperatures move up and down at each LFC optimization time step (10 min), impacting heat pump operation. For reference, compare the T_{csp} variations for baseline (green T_{set} line), LFC and RTC in Fig. 4.

Table 1 Market time step-to-time step average power flow change, voltage standard deviation and voltage violations outside Range A.

	July 6 avg Power Flow[a] change (kW)	July 7 avg Power Flow[a] change (kW)	July 6 Voltage std. dev.[b] (V)	July 7 Voltage std. dev.[b] (V)	July 6 Voltage violations[c]		July 7 Voltage violations[c]	
					Count (per h)	Duration (min/h)	Count (per h)	Duration (min/h)
baseline	101	101	0.94	0.99	0.29	0.80	0.22	0.65
RTC	745	870	2.4	3.0	1.80	7.2	2.16	9.2
LFC-RTP_{avg}	423	447	1.47	1.58	1.11	3.3	1.16	3.7

a. timestep-to-timestep change, absolute value, at substation
b. based on average voltage across all house meters
c. average per house across the day

The left-hand columns of Table 1 give a measure of the power flow volatility, showing the average change in power flow from one time step to the next across all houses (compare to 8 MW peak load). RTC produces stronger fluctuations than LFC and LFC stronger than baseline. This power flow volatility leads to voltage volatility, with voltage standard deviation given in the center columns and resulting voltage violation counts and durations as shown in the right columns of Table 1. The corresponding time step-to-time step voltage change (absolute value, averaged across all house meters) on July 7: baseline 0.30 V, LFC 1.72 V, and RTC 2.3 V. This in turn is 2.5 %, 14.3 % and 19 % of Range A. Also notice that, despite the stronger price fluctuations on July 7, the power flow fluctuations and the voltage variability and violations on July 6 are only slightly lower than what is observed July 7. The reason for this can be tied to the operation of the two controllers producing similarly volatile T_{csp} profiles on July 6th versus July 7th (Fig. 5 and Fig. 4). The relationship between temperature and voltage is studied more in section 3.2.3.

3.2.2. Substation Power Flows

Fig. **6** shows the volatility in substation power flows. The baseline demonstrates a classic duck curve with load decrease in the morning followed by an increase up to when the sun sets at 8 p.m. In addition, power fluctuations are minimal (refer back to Table 1). In contrast, the fluctuations in power flow at the substation are greater for the LFC and even stronger for the RTC. There are also significant negative power excursions in response to the RTC, indicating power flow back to the transmission grid. The substation power flow and voltage fluctuations are not incorporated as constraints in the LFC and RTC. This analysis shows the indirect impact of grid condition-unaware controllers on voltage. Note that the truncation of LFC and RTC power flow results are due to grid solver convergence issues in the presence of the very large power flow reversals. Nonetheless, the power flow fluctuations are as expected as thermostats react to price signals and turn heat pumps off and on.

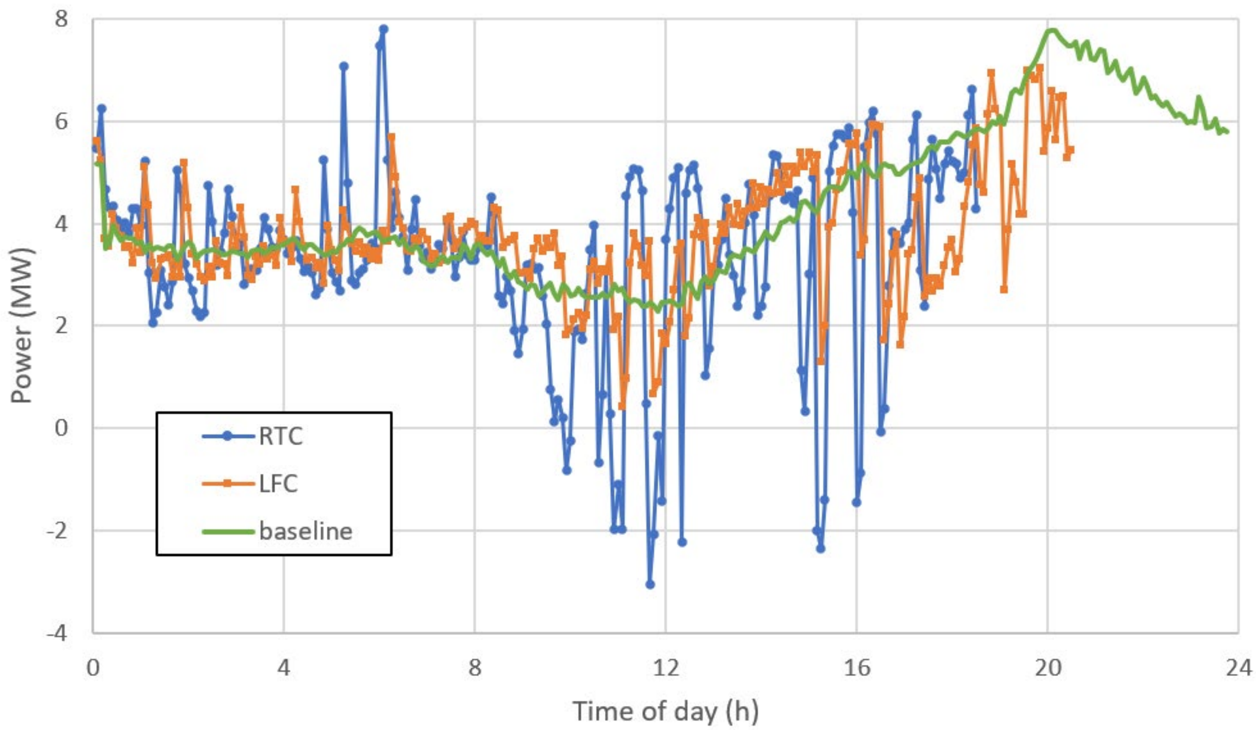

Fig. 6 Substation real power flow for July 7, comparing baseline (no price response) to RTC and LFC controller adjustment of home temperatures in response to price.

These power flow changes result in voltage fluctuations. Voltage regulator action is increased 3x over baseline for LFC and more than 5x over baseline for RTC. The average voltages across all 1977 house meters are given in Fig. 7 (RTC) and Fig. 8 (LFC). July 6 had fewer fluctuations than July 7, and LFC fewer fluctuations than RTC, as also seen in Table 1. Note again that the GridLAB-D inverter model does not curtail PV generation at Range A upper limits, so voltages above this level can be viewed as indicating where curtailment would occur and customer revenue lost. Also note that RTP and DAP are wholesale market prices. Clearing prices include the impact of PV generation across the wholesale market territory, but do not reflect the significantly higher penetration on this distribution feeder.

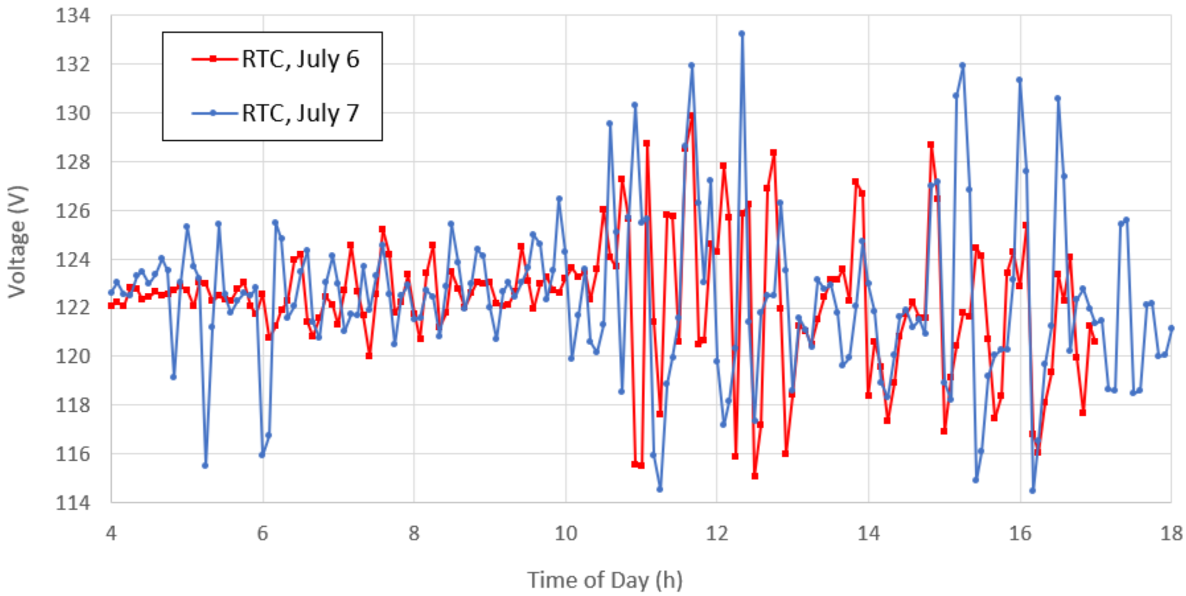

Fig. 7 Average hourly voltage across house meters, 8500 grid using RTC.

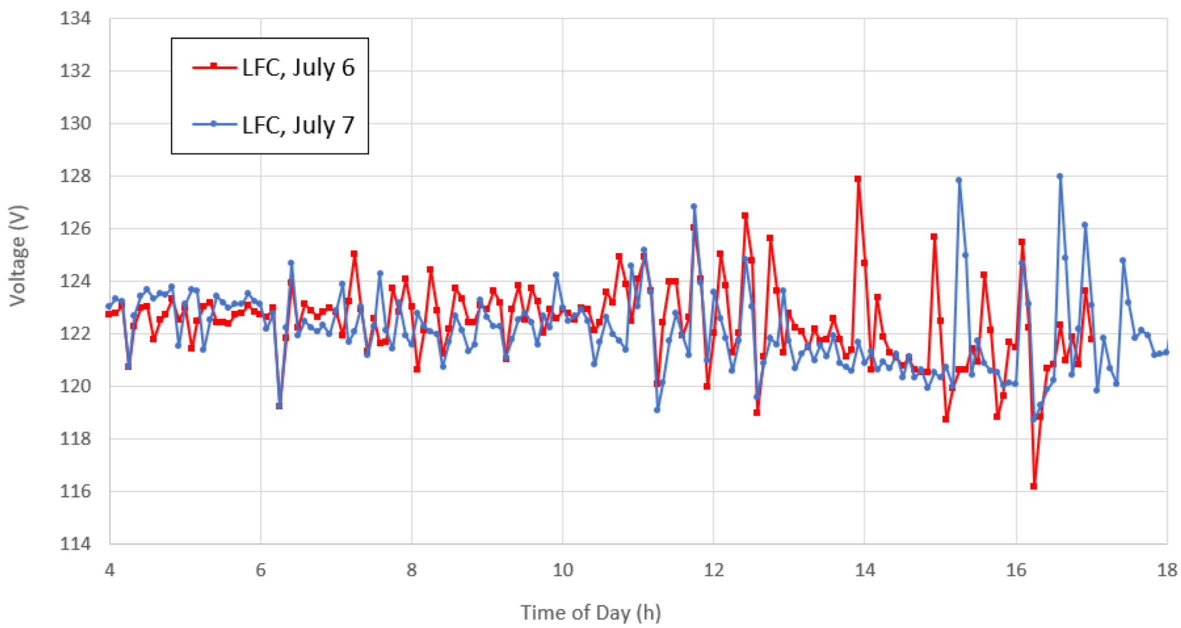

Fig. 8 Average hourly voltage across house meters, 8500 grid using LFC.

3.2.3. Correlation of Voltage and Price Movement

Consider the T_{csp} profiles (baseline, LFC, RTC) for the house shown in Fig. 4, and Fig. 5. For the baseline case, each home has a flat setpoint temperature across the day (T_{set}), which produces the stable power flow seen in **Fig. 6**. For RTC, the adjusted T_{csp} moves in proportion to the RTP (except when the temperature is clipped at T_{max}). Raising T_{csp} leads to heat pumps shutting off, while lowering T_{csp} leads to heat pumps turning on. A large movement in price of electricity results in a large movement in T_{csp}. If a price jump follows a large price drop, there is likely to be a change from all heat pumps ON to all heat pumps OFF in a single action with a resulting drop of approximately 6 MW load. This behavior can be observed in several instances in **Fig. 6**. The result is synchronization of heat pumps (or more generally, all price-responsive loads) on the grid.

Fig. **9** overlays the average July 7 RTC T_{csp} profile of all houses with the substation real power flow. The correlation of changes in temperature at each 5-min step to changes in power flow has a correlation coefficient of R = -0.83.

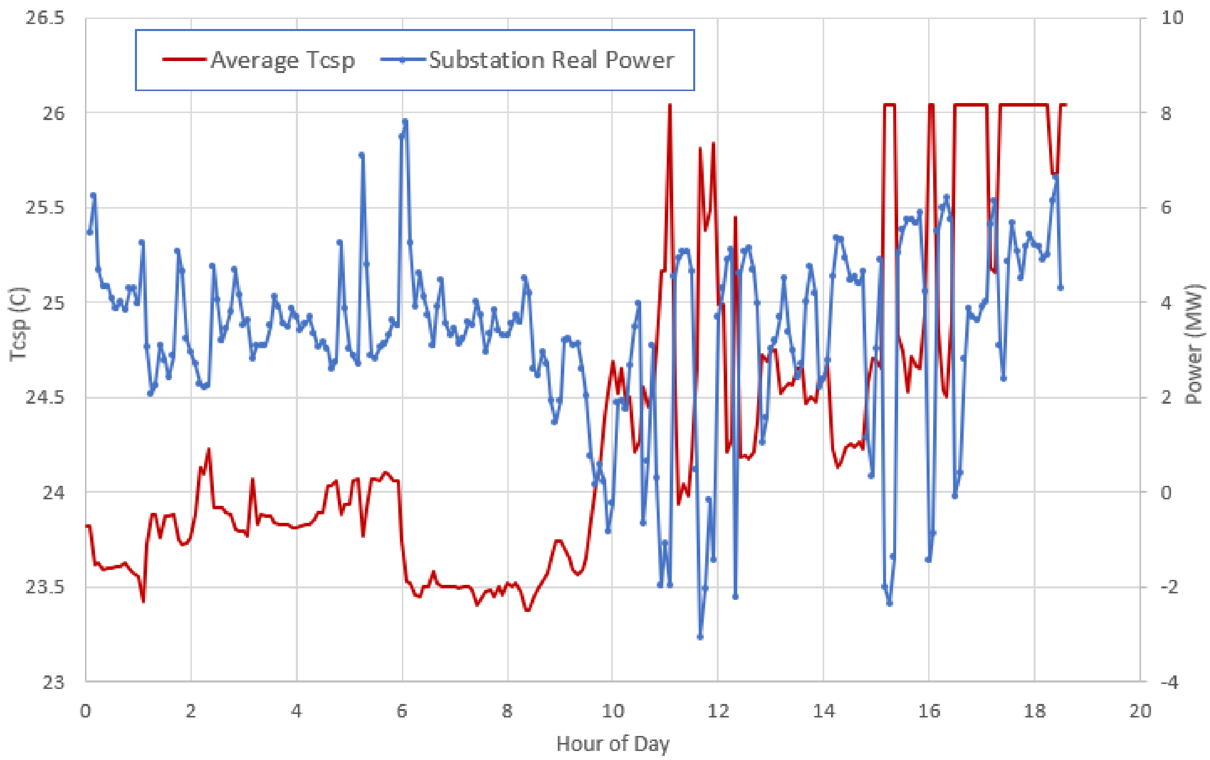

Fig. 9 RTC average T_{csp} across all 8500 grid houses compared to the resulting substation real power flow at each 5-min interval, July 7.

The T_{csp} is itself driven by price, per Eqn. 1. RTP changes drive T_{csp} changes which lead to power flow changes. And voltage changes are strongly correlated with these power flow changes, with a correlation coefficient R = -0.91. The combined correlation of voltage to price is relatively low, R = 0.36. The large majority of price changes are on the order of 0.01 $/kWh, and these have essentially no correlation to voltage changes.

In the case of the LFC controller, T_{csp} is determined for each house independently by optimizing the temperature profile across the next day using RTP_{avg}. The T_{csp}, averaged across all houses, is shown in Fig. 10 along with the RTP_{avg} price. There is only a weak correlation between RTP_{avg} and T_{csp}. One sees the LFC controller precooling prior to the peak price period and then allowing the house temperature to rise during the peak prices.

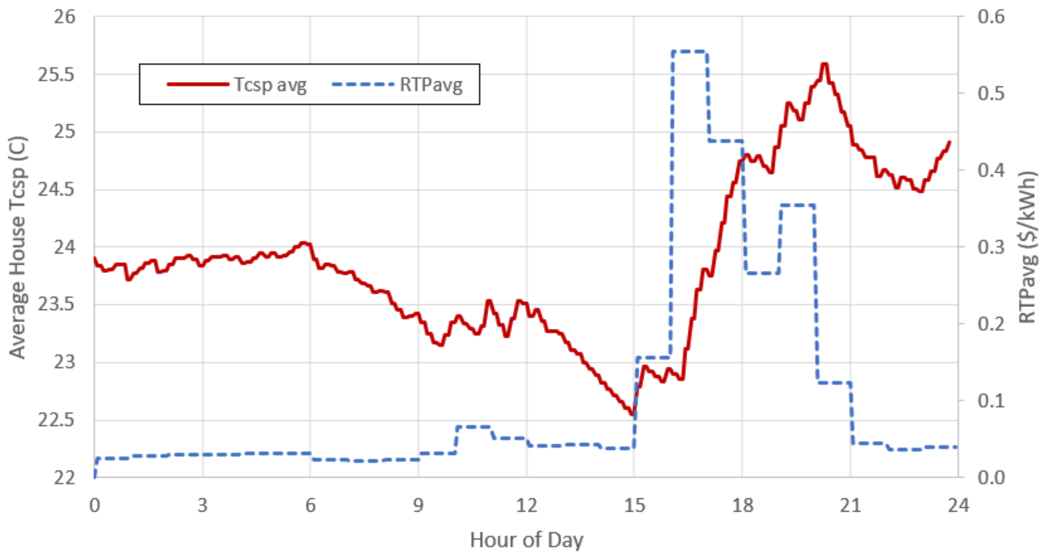

Fig. 10 LFC average house T_{csp} with corresponding RTP_{avg} price, July 7, 8500 grid.

The average LFC T_{csp} is shown with the corresponding substation power flow in Fig. 11. In this case, one can see that many of the temperature drops are accompanied by power flow jumps. In fact, in most cases, each change in direction of the T_{csp} trend (from down trend to up, or up to down) is accompanied by a change in power flow on the order of 1 MW. The correlation coefficient for change in power flow with change in T_{csp} is R = -0.45, but there is no significant correlation of change in T_{csp} with voltage. However, if one takes only the change in T_{csp} at the point of temperature trend inflection (uptrend to down or *vice versa*) and correlates that to change in voltage, the correlation is very strong, with R = 0.94.

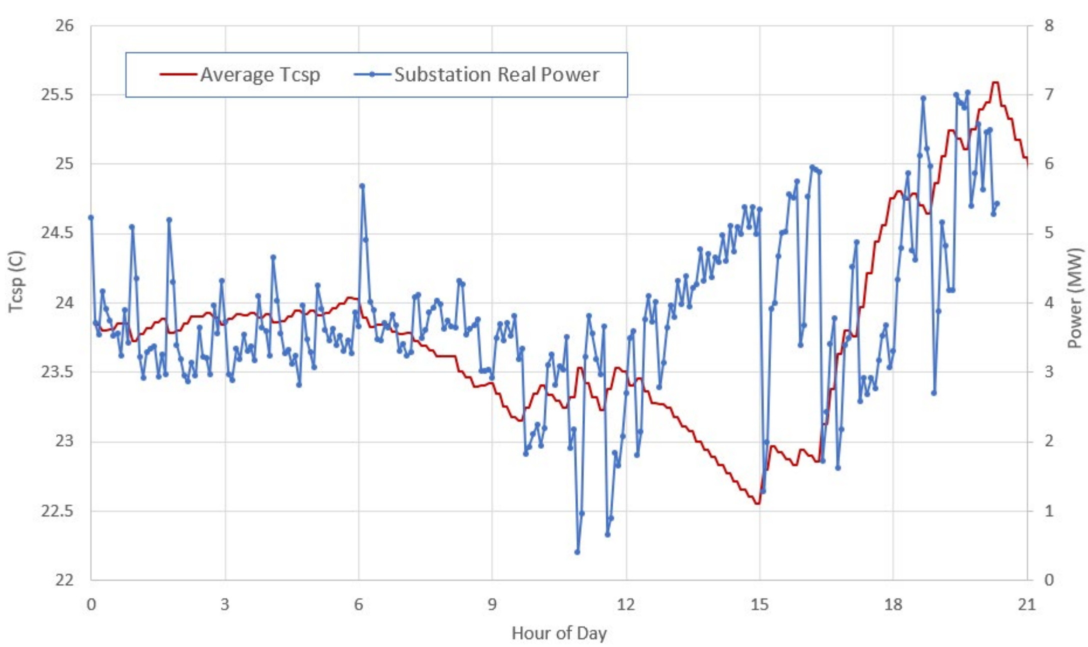

Fig. 11 LFC average T_{csp} across all 8500 grid houses together with the resulting substation real power flow at each 5-min interval, July 7.

Using this approach with the RTC data does not produce any improvement in the RTC correlation of price to voltage. This is due to the volatile RTP with few extended up or down trends in T_{csp} (e.g., compare RTC T_{csp} to LFC T_{csp} in Fig. 4 and Fig. 5).

A key point to be made here is that, despite the relatively gentle LFC T_{csp} movements (compared to the RTC), the voltage is nonetheless highly correlated with T_{csp}, which is itself driven by the hourly price signal. Synchronization across houses is an issue when there are changes in the T_{csp} trend from cooling to warming (or *vice versa*), as evidenced by resulting significant changes in power flow. These changes then cause voltage fluctuations and voltage violations (Table 1).

This finding raises the question of whether a smoothed price signal might reduce RTC voltage disturbances. To answer this, two additional tests were performed with the RTC controller using exponential moving average (EMA) smoothing on the RTP signal. The EMA price (pEMA) is calculated as follows:

$$pEMA = RTP \times m + pEMA_{t-1} \times (1 - m) \tag{2}$$

where m is the smoothing multiplier equal to 2/(t +1), where t equals the number of time steps to include in the smoothing, and $pEMA_{t-1}$ is the price from the previous time step. For these tests, simulations were performed with t = 3 (a 15-minute smoothing, designated as EMA3) and t = 12 (a one-hour smoothing, EMA12). These price signals are shown together with the July 6 RTP signal in Fig. 12.

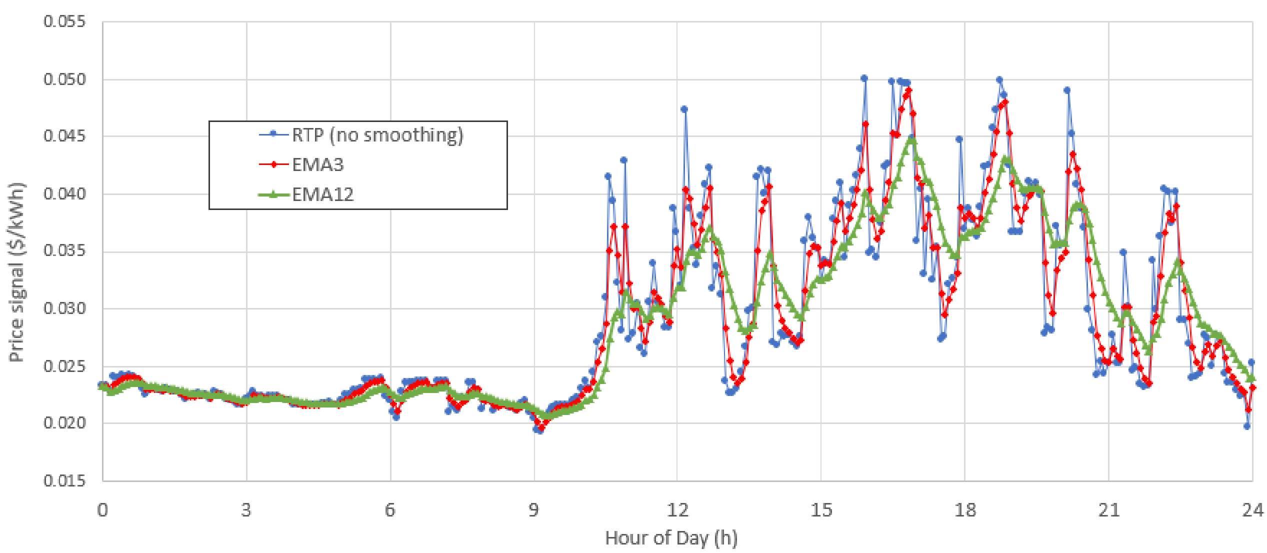

Fig. 12 July 6 RTP, EMA3, and EMA12 prices.

Fig. **13** shows a significant reduction in voltage disturbance moving from RTP to pEMA3 to pEMA12 as also summarized in Table 2.

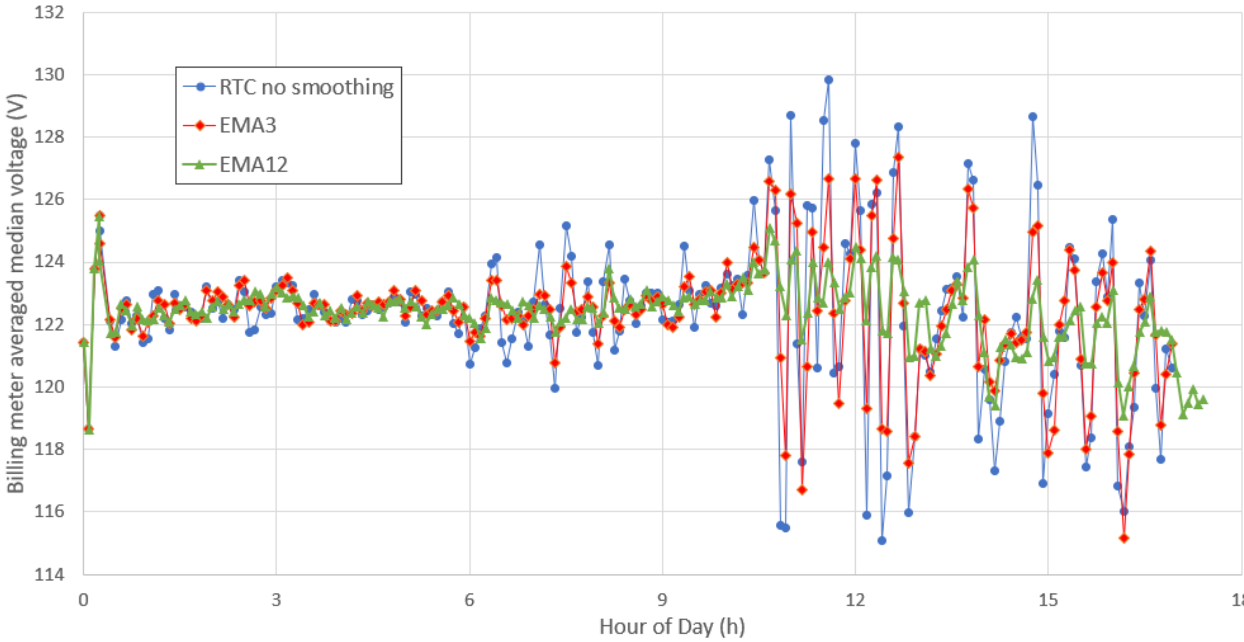

Fig. 13 Average voltage levels across the day for RTC July 6, comparing input price signals RTP, EMA3 and EMA12 (RTP smoothed with 3-time-step and 12-time-step averaging).

Table 2 Voltage violations outside Range A, average substation change in power flow time step-to-time step (abs. value), and standard deviation of average house voltage, July 6 RTC.

Price signal	Average change in power flow (kW)	Average voltage standard deviation (V)	Voltage violation count (per h, per house)
RTP (no smoothing)	745	2.40	1.80
EMA3	515	1.80	1.19
EMA12	241	0.99	0.65

These simulations were not performed for the LFC since the RTP_{avg} price is already an hourly average. However, it is not a moving average, leading to significant price steps on the hour and voltage volatility as seen earlier (compare EMA12 here to LFC in Table 1).

3.3. Discussion

These experiments provide some insights into potential power quality issues that may be encountered when deploying price-based control algorithms.

Use of dynamic price control can deliver significant adjustment of feeder load to benefit the bulk grid, but bulk market prices do not consider distribution voltage. Voltage violations are a key factor determining hosting capacity, and it appears that response to dynamic prices has the potential to reduce hosting capacity. These results raise several questions that should be considered.

1. Is this behavior real, or is the simulation contrived and the results unlikely to ever be realized on an actual distribution grid?

This research has shown strong voltage variability tied to price volatility or simply to price changes. Do we see evidence of this behavior in areas where dynamic tariffs exist today? Is the simulation representative of reality?

The simulated grid is based on a real distribution grid, except that the amount of PV generation has been increased. Additionally, a large amount of price-responsive load is included. We can observe now that some utilities and local public utility commissions recognize the importance of accessing customer DER flexibility and the value of a dynamic price signal. Some utilities are using a real-time 5-min price based on RTP [8]. Some are using a day-ahead hourly signal based on DAP [23]. Some are using an hourly signal based on RTP_{avg} [24]. All of these are in play and may become more common.

For current dynamic price tariffs, there is a small number of customers enrolled, and/or few automated controllers that act on the price signal. The actual percentage of load that is tuned to the price signal is low such that one could expect no noticeable voltage impact. On the other hand, a reasonable end goal might be that every large load (heat pump, air conditioning, water heater, batteries, pool pumps) has a smart controller planning load and generation based on price. And every controller will watch the same price signal. When the day arrives that we have 75 % of system load controlled by price-responsive controllers, then we will face the same situation seen in this research. A diversity of controllers will help to smooth load changes, but as long as they all watch the same price signal, the results will be similar.

An alternative implementation may see different aggregators managing sets of loads dedicated to other grid services, not only energy provision in response to wholesale energy market prices. For example, one aggregator may manage some load or generation to provide primary frequency support, while another provides regulation, or wind firming. This implementation should reduce the amount of DER flexibility responding to energy prices and thus help to reduce voltage variability.

2. How might we best use bulk market dynamic price tariffs?

Adjusting demand based on wholesale market prices can serve bulk capacity needs but may induce voltage variation for a distribution grid that is already having voltage issues at peak load or peak sun. The severity of voltage variability depends in part on voltage control hardware and load on the grid. Additionally, the size and frequency of price changes will drive voltage changes. Load synchronization can occur when the frequency of price changes aligns with (equal to or less than) the frequency of the charge/discharge and heat/cool cycles of batteries and thermal storage. And every battery/load will seek to charge/run at the lowest price time in their charging window. Therefore, grid hardware may need upgrading and the price signal may need smoothing and adjustment to minimize voltage disruptions.

Beyond this, grid operators may consider adjusting price signals based on local voltage levels with some spatial granularity: lower prices at a PV hot spot (high voltage) or higher at an EV load pocket (low voltage). The adjustment could be made such that the average price at all points on the grid is the same across a day while the amount of price variation may be more or less in one location or another.

Another solution may be to avoid billing a customer based on 5-min RTP, which incentivizes fast response to price changes. An alternative, as used in [24], may be to communicate the RTP, but to bill based on the hour's resulting RTP_{avg}. In this way, smart devices may react less strongly to every price change.

Finally, a distribution utility may also consider installing battery banks to respond to voltage, providing real and reactive power to minimize voltage variability.

3. Are there other ways to engage DER flex that may supplement or work better than passing bulk market prices?

The approach of passing bulk market clearing prices down to controllers does not consider distribution congestion. There is no feedback into the market. Perhaps the distribution utility can monitor power flows and voltages and these data can be used to modify real-time prices. But this approach still does not allow for coordination between users (e.g., "you charge now, and I'll charge next hour"), and it would not be useful if DER are only responding to day-ahead prices.

An alternative is to bring the market down to the retail level. Local controllers buy and sell power in a day-ahead and/or real-time market. A distribution utility may offer power for sale tomorrow from 1:00-2:00 pm for 0.10 $/kWh, but with a quantity limit. As the committed power delivery approaches some congestion limit, then additional power sold in that time interval increases in price. Different controllers use the market to find lower price options that fit their schedules, and through this market mechanism the power use is coordinated and congestion is avoided while providing optimal prices for consumers.

Some researchers and even companies are testing different types of market systems that can deliver this desired result, but it also requires automated equipment that understand the local market design. Ideally, we can have standards for how market information is exchanged with a limited number of market platforms.

Some principles can be discerned from this discussion.

1. Price variation incentivizes flexibility to help balance the grid, moving load to lower price periods, but price-responsive controllers can impact grid voltage.
2. Bulk market prices communicate capacity needs but do not consider distribution grid constraints. Some price signals may not be suitable for more-constrained grids.
3. An increased number of price-responsive controllers and larger changes in price both lead to bigger power flow changes and resulting voltage variability.
4. A more volatile price signal will tend to induce more synchronized load response with corresponding voltage volatility.

4. Conclusion

Two price-responsive heat pump controllers were tested in simulation, one responding to a day-ahead hourly price signal (LFC) and the second to a real-time 5-minute signal (RTC). Both controllers induced power flow fluctuations with resulting voltage fluctuations, more so for the RTC than the LFC. LFC voltage violations (Table 1) increased on the order of 400 % above baseline. The RTC controller doubled that again for voltage deviations, voltage regulator actions and capacitor bank actions leading to reduced power quality.

Analysis of the impact of dynamic prices on voltage suggests these results are indicative of voltage problems on a future grid with a high percentage of price-responsive loads if care is not taken to manage volatility of the price signal and if the grid is near its hosting capacity. Results show that large price changes, or a shift in price trend from rising to falling (or *vice versa*) can result in synchronized load response, with devices turning on or off together. This can result in large shifts in power flow at the substation. The grid must be able to handle these jumps in power flow and resulting voltage changes. Simulations with smoothed RTP showed significantly reduced voltage volatility.

A diversity of grid services (e.g., aggregators providing wind firming) may reduce the impact, as will smoothing of the price signal. Additionally, the price signal may be varied locationally to better manage voltage. A potentially better, but likely more complex solution, is to implement a local market within the feeder, or at a more granular level, in order to manage congestion. These solutions will be explored in future research.

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