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Power Factor Correction in Feeders with Distributed Photovoltaics Using Residential Appliances as Virtual Batteries

Andrew P. Reiman[1], Member, IEEE, Abhishek Somani[1], M.J.E. Alam[1], Member, IEEE, Peng Wang[1], Member, IEEE, Di Wu[1], Senior Member, IEEE, and Karanjit Kalsi[1], Senior Member, IEEE
[1]Pacific Northwest National Laboratory, Richland, WA 99352 USA

Corresponding author: Andrew P. Reiman (e-mail: andrew.reiman@ pnnl.gov).

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ABSTRACT Thermostatically controlled residential appliances have built-in thermodynamic storage that, even within a narrow temperature band that need not degrade the comfort level of occupants, can be used to provide a variety of value streams to power system operators and customers. In this work, residential air conditioners and electric water heaters are used to improve feeder power factor in a distribution system where photovoltaic systems cause the feeder power factor to dip daily, increasing losses. Improving distribution feeder power factor improves the efficiency of the transmission and bulk generation systems. A daily optimal dispatch regime is used to maximize the daily minimum feeder power factor. Following this regime, electric water heaters cool off in preparation for a low-feeder-power-factor event, turn on to improve the power factor during the event, and return to a neutral condition after the event. Air conditioners, which have a power factor lower than the feeder overall, are optimally dispatched in inverse pattern. Using a model of a real commercial and residential distribution feeder in the western United States, optimal dispatch of virtual batteries is shown to be capable of improving the daily minimum power of that feeder by as much as 0.026. The power factor correction and optimal dispatch techniques are based on a robust virtual battery framework, making them portable to other applications such as volt-var optimization and transactive energy systems.

INDEX TERMS Energy storage, optimal scheduling, power distribution, power generation dispatch, power system management, power system modeling.

I. INTRODUCTION

Distributed photovoltaic (PV) systems enable electric utility customers to produce power onsite, reducing electricity bills as well as the aggregate net load of the feeder. This paradigm can benefit customers and society at large [1]; however, distributed generation also introduces technical challenges [2]. Among these challenges, the real power injections from distributed PV systems cause both voltage rise [3] and power factor degradation [4], conflicting issues that are both commonly addressed using capacitors [5]. The virtual battery (VB) framework [6], [7], [8] leverages the thermodynamic energy capacity of thermostatically controlled appliances and offers a mechanism to counteract power factor degradation caused by distributed PV systems without contributing to voltage rise.

The power factor of a load on an alternating current power system characterizes a relationship between the real power delivered to the load and the amplitude of the current required to supply that power [9]. When the power factor deviates from unity, additional losses are incurred in the conductors serving the load [10]. The power factor of distribution system feeders impacts the efficiency of the generators and transmission lines that serve them. Capacitors can be used to improve the power factor of a distribution system by injecting reactive power [5]. Techniques have long been developed to optimally size and place capacitors for loss minimization [11], [12], [13]; however, these traditional techniques assume that correcting the system power factor will never cause overvoltage.

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While fixed capacitors affect system voltage and var flow, substation automation introduced an opportunity to coordinate voltage and var control [14]. Combining var control with conservation voltage reduction yields methods to optimize the settings of voltage and var controlling equipment (volt-var optimization, VVO) [15]. More recent VVO algorithms extend control beyond the substation and optimize a formal objective such as minimizing loss and/or a voltage profile metric [16], [17]. Consideration is traditionally limited to system infrastructure including voltage regulators and capacitors. More recent work also includes reactive power from PV inverters [18], [19] and battery storage [20].

VVO traditionally dispatches utility-owned resources only. Demand response allows system operators to modulate load along with generation to achieve power balance. Early interest in demand-side management of utility load focused on marketing to influence customer behavior [21]. Smart grid concepts and communication infrastructure enable demand response via direct load control using a price signal or load-shedding command [22]. Optimal direct load control has been proposed as a way to manage peak load by throttling water heaters [23], and later a combination of water heaters, air conditioners, and other end-use loads [24]. Improvements that control load by modifying setpoints were introduced in [25]. Leveraging demand response to enhance VVO is demonstrated in [26] (using a multi-objective optimization) and [27] (using a game theory approach). The role of demand response in energy markets is discussed in [28] and demand response of elastic and inelastic loads to achieve optimal power flow is discussed in [29].

The traditional concept of demand response treats dispatchable load as a virtual power plant and allows appliances to return to their normal thermodynamic cycle during a ‘‘payback’’ period. Reimagining thermostatically controlled loads as VBs [6], [7], [8] expands both the range of behavior profiles for the loads (e.g., VBs can ‘‘charge up’’ to prepare for a discharging event) and the range of services that can be provided by the appliances. In this paper, thermostatically controlled loads are represented as VBs that can provide distribution system services including power factor correction. Specifically, thermostatically controlled residential appliances are treated as VBs that can mitigate power factor degradation caused by distributed PV systems. Improving the feeder power factor reduces the transmission current required to supply the feeder, reducing transmission and distribution losses.

The specific contributions of this paper are a power factor correction framework for distribution feeders and an optimal dispatch method for thermostatically controlled loads based on a VB framework.

VB power factor correction is portable to other applications. In VVO, VBs could be co-optimized alongside other resources. And in transactive energy systems, VBs could participate in markets to provide power factor correction as one of a number of services. The optimization methods presented here are based on a robust abstract VB framework and the optimization methods themselves are portable and can be easily extended to other applications.

The rest of this paper is organized as follows. In Section II, thermostatically controlled residential appliances are characterized as VBs. In Section III, optimal feeder power factor correction using VBs is introduced. In Section IV, a demonstration of these concepts is discussed. Section V contains concluding remarks.

II. APPLIANCES AS VIRTUAL BATTERIES

A VB model uses the thermodynamic energy storage of thermostatically controlled systems to modulate load on the power system. A VB charges by turning appliances on that would otherwise be off and discharges by turning appliances off that would otherwise be on. As defined in [8], a VB is a set of power profiles in which each profile P satisfies (1)-(3).

$$\underline{P}(k) \leq P(k) \leq \bar{P}(k) \tag{1}$$

$$\underline{E}(k) \leq E(k) \leq \bar{E}(k) \tag{2}$$

$$E(k+1) = \alpha E(k) + P(k)\,\Delta t \tag{3}$$

where k is the discrete time step, $P(k)$ is the VB power at step k bounded by its upper and lower limits, $E(k)$ is the VB energy state at step k, bounded by its upper and lower limits, α is the self-discharge rate, and Δt is the time step size. Additional detail on the VB model can be found in [8].

The power and energy limits and the self-discharge rate are determined by the characteristics of participating appliances. The energy limits are symmetric about zero and proportionate to number and volume of the units participating at a given point in time. The span of the power limits is determined by the number and heating capacity of the participating appliances at a given point in time and the position of that span relative to zero is determined by the amount of power required to keep the VB energy at its neutral position. The ability of a particular appliance to participate at a given time depends on the thermostat setpoint compared to the ambient or exterior temperature. For example, when it is cold outside, an air conditioner is neither on nor available to turn on.

A feeder from the western United States used to illustrate the virtual battery equations. The feeder is also used for a case study in Section IV. The temperature profile for part of the summer shown with the weighted average temperature setpoint of the air conditioner fleet on a feeder is shown in Fig. 1.

Air conditioners become available as indoor temperatures begin to exceed air conditioner cooling setpoints. Indoor temperature lags outdoor temperature for insulated homes.

A. ELECTRIC WATER HEATERS

A water heater is a thermostatically controlled appliance that heats and stores water for use on demand. Water is typically heated by a resistive element. Temperature setpoints and deadband of the electric water heaters are used to estimate VB parameters. The ambient temperature outside of the water heater (air temperature of the home or garage where the water

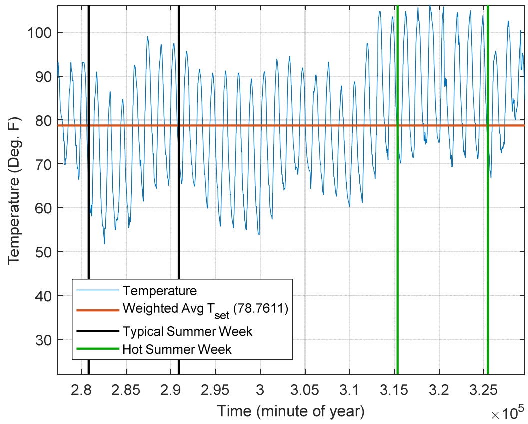

FIGURE 1. Outdoor temperature profile for part of the summer; T_{set} is device-specific and holds a range of values across the fleet.

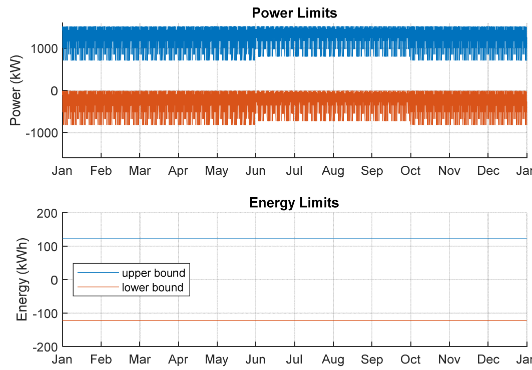

FIGURE 2. Power limits (top) and energy limits (bottom) for the electric water heater based VB in the demonstration feeder.

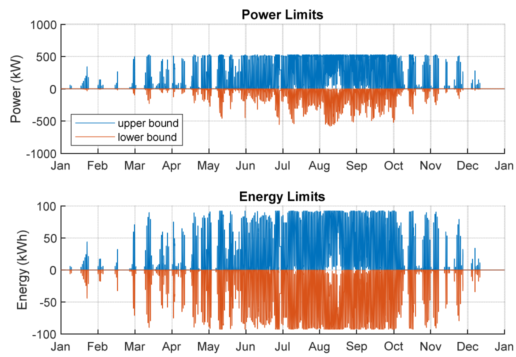

FIGURE 3. Power limits (top) and energy limits (bottom) for the air conditioner based VB in the demonstration feeder.

heater is located) is never expected to exceed the thermostat setpoint of the unit. However, if the water draw is large, the water heater may not have any flexibility to participate in the VB.

1)POWER FACTOR

Electric water heaters typically use resistive heating elements with unity power factor.

2)POWER AND ENERGY LIMITS

The thermodynamic energy storage capability of a water heater depends on the volume of water and the upper and lower temperature limits for the appliance.

The power limits span depends on the sum of the heating capacities of all of the water heaters and is nominally constant. The actual power consumption of water heaters depends on the supply voltage, bounded by the operational voltage limits of the feeder (0.95 per-unit to 1.05 per-unit). When hundreds of devices are aggregated across a feeder, some devices will draw additional power and others will draw less than the nominal power. Because water heaters are off more often than they are on, the power limits are generally biased in the positive direction with a lesser bias at times of common hot water usage.

The power and energy limits for the electric water heater VB resource are shown in Fig. 2.

The positive power limit usually has a greater magnitude than the negative power limit. This is because of the low duty cycle of water heaters; there are typically more water heaters to turn on than there are to turn off at any given time. The power limits also change throughout the day. When people are at home and using more hot water, the power limits shift in the negative direction. The energy limits are proportionate in magnitude to the aggregate thermal capacity of the devices in the VB. Because the number of participating water heaters is constant, the energy limits are constant.

B. AIR CONDITIONERS

An air conditioner is a thermostatically controlled appliance that cools the air inside a building. The availability of an air conditioner depends on the outside temperature relative to the thermostat setpoint. Availability throughout a fleet of air conditioners varies seasonally and daily.

1)POWER FACTOR

Air conditioners rely on machines including condensers and fans and have a lagging power factor. In this work, air conditioners were modeled with a power factor of 0.8.

2)POWER AND ENERGY LIMITS

The VB power and energy limits vary with time of day and season based on the air conditioning use as shown in Fig. 3.

At peak usage during summer months, the VB capacity at this location may be compared to a 500-kW, 100-kWh battery.

III. FEEDER POWER FACTOR CORRECTION

Feeder power factor describes how much current is required to supply a given amount of power. The feeder power factor depends on the net feeder load.

$$p.f. = \frac{P}{|V| \cdot |I|} = \frac{P}{\sqrt{P^2 + Q^2}} \tag{4}$$

where P is the net real power, Q is the net reactive power, V is the voltage, and I is the current. Power factor is maximized when current and voltage waveforms are aligned. Improving this alignment reduces the current magnitude required to deliver a fixed amount of real power and improves efficiency of transmission and distribution. Distribution feeder power

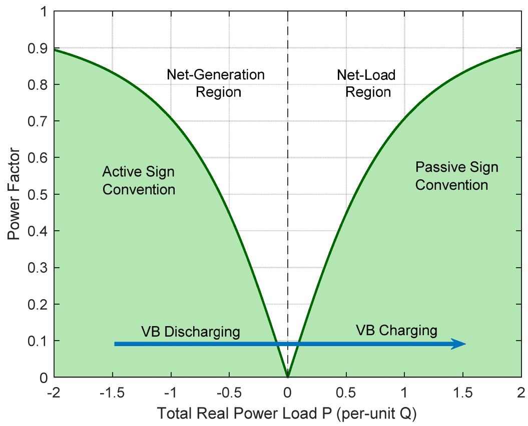

FIGURE 4. Feeder power factor as a function of P for fixed Q (green); shown with active sign convention (positive for net power export) in the net-generation region and with passive sign convention (positive for net power import) in the net-load region; for unity power factor VBs, charging increases total real power load and discharging decreases total real power load.

factor correction is the act of controlling feeder power factor to reduce transmission system losses.

The magnitude of power factor lies on the range between zero and one and is further characterized by the direction of real power flow: if the real power net load of the feeder is positive, the passive sign convention is used; if the net load of the feeder is negative, the active sign convention is used. The net load is a combination of the uncontrolled load, the distributed generation, and the load of all VBs.

$$P = P_L + P_{VB} \tag{5}$$

$$Q = Q_L + Q_{VB} \tag{6}$$

where P_L is the uncontrolled feeder net real load, Q_L is the uncontrolled feeder net reactive load, P_{VB} is the total real load of all VBs, and Q_{VB} is the total reactive load of all VBs. Uncontrolled feeder load includes PV generation, loss, customer load that is not participating in the VB, and load from devices that are participating in the VB necessary to keep the VB at neutral power output and neutral energy state. Note that small changes in uncontrolled load (e.g., line losses) resulting from changes in VB load are not captured in this VB model. The relationship between P_{VB} and Q_{VB} depends on the power factor of each of the VBs.

$$P_{VB}(k) = \sum_i P_{VB_i}(k) \tag{7}$$

$$Q_{VB}(k) = \sum_i P_{VB_i}(k) \tan\left(\cos^{-1}\left([p.f.]_{VB_i}\right)\right) \tag{8}$$

$$\tag{9}$$

where k is the discrete time step, i is the VB index and $[p.f.]_{VBi}$ is the power factor of VB$_i$.

Fig. 4 shows the effect of changing P while holding Q constant. Note that P decreases as P_{VB} enters its discharging region.

A traditional feeder has a positive P_L and a positive Q_L; that is, it has a lagging power factor in the net-load region of Fig. 4. Distributed PV systems operating at unity power factor reduce the feeder total real power load without changing the total reactive power load, reducing the feeder power factor or eventually shifting the feeder to the net-generation region. Notably, smart inverter settings, including fixed non-unity power factor or volt-var control, can exacerbate the feeder power factor by canceling real power load while increasing the reactive power load.

A. MAXIMIZING MINIMUM POWER FACTOR

Like physical batteries, VBs are limited by both power and energy. They cannot be charged or discharged indefinitely. However, VBs can be charged daily to level the minimum power factor and then recharged later in the day. Solving the following optimization problem maximizes the minimum power factor for a given period.

$$\max_{\tau, P_{VB}(k)} \{\tau\} \tag{10}$$

subject to the VB power and energy limits (1)-(3), physical constraints (4)-(6), joint VB equations (7)-(8), and:

$$0 \le \tau \le 1 \tag{11}$$

$$p.f.(k) \ge \tau \forall k \tag{12}$$

where τ is a minimum power factor threshold, $P_{VB}(k)$ is the VB load power at time step k, $p.f.(k)$ is the feeder power factor at time step k, and α is 1. Power and energy limits are defined by the physics of the distributed energy resources participating in the VB.

B. MINIMIZING AVERAGE STATE OF CHARGE

In the first stage of optimization described above, $P_{VB}(k)$ is generally under-constrained. To determine an optimal dispatch, the absolute virtual state of charge, or energy, of each VB can be minimized in a second stage of optimization (13) subject to $\tau*$ (from the first stage of optimization). This ensures that the VBs (a) are maximally available for other services and (b) have a minimal impact on customers and their appliances participating in the VB.

$$\min_{P_{VB}(k)} \sum_{k,i} \left| E_{VB_i}(k) \right| \tag{13}$$

subject for any time step k to the VB power and energy limits (1)-(3), physical constraints (4)-(6), joint VB equations (7)-(8), and:

$$p.f.(k) \le \tau^* \forall k \tag{14}$$

where $\tau*$ is the optimal minimum power factor threshold, $P_{VB}(k)$ is the VB load power at time step k, $p.f.(k)$ is the feeder power factor at time step k, and α is 1. Power and energy limits are defined by the physics of the distributed energy resources participating in the VB.

IV. VIRTUAL BATTERY DISPATCH DEMONSTRATION

VB dispatch was demonstrated using a GridLAB-D [30] model of a real distribution feeder. Water heaters and air conditioners were modeled as agent-based appliances and allowed to follow their normal thermostat-controlled behavior. The power flow solver was set to Newton-Raphson mode. The model was simulated to obtain the baseline weekly power factor profile. The optimal dispatch of VBs was computed using a generic non-linear program solver, first for an electric water heater based VB, then for an air conditioner based VB, and finally for a co-optimal dispatch of both VBs acting together. Voltage-controlled capacitors switching operations are assumed to prioritize voltage control and remain unchanged with the introduction of VB dispatch. VB dispatch is optimized each day and computed assuming neutral charge at midnight.

A. DEMONSTRATION FEEDER

A demonstration feeder located in the western United States was used to demonstrate VBs. To study VB capability, electric water heaters were modeled for all residential customers to represent a hypothetical water heater electrification scenario. This demonstration feeder model has the following attributes:

–Primary voltage: 12.47 kV
–Residential houses: 340
–Residential houses with electric water heating: 340
–Total electric water heater capacity: 1.53 MW
–Residential houses with electric air conditioning: 152
–Total electric air conditioner capacity: 1.73 MW
–Total distribution transformer capacity: 23.5 MVA
–Residential transformer capacity ratio: 0.4575
–Commercial transformer capacity ratio: 0.5425
–Distributed PV: ∼20% peak load capacity
–Distributed capacitors: two banks, voltage controlled

The model includes behavioral residential loads with explicit representation of heating, ventilation, and air conditioning systems and other end uses. The feeder is less than half residential (by transformer capacity) and fewer than half of houses have electric air conditioning. The impact that a VB can have on a system depends on factors including the fraction of load that the participating appliances form and the power factor of the VB.

B. BASELINE SIMULATION

The feeder model was simulated without VB actuations for a warm summer week. The simulated PV generation profile is shown in Fig. 5.

The simulated PV power and feeder power factor is shown in Fig. 6.

The feeder power factor shows diurnal variations. In each of the days simulated, the power factor begins low at night and increases slightly as load begins to increase in the morning. As unity-power-factor PV systems begin to produce power, the power factor decreases, leading to the daily minimum. When the voltage-controlled capacitors engage, the power factor rises sharply until the capacitors switch off again at night. At mid-day, fluctuations are caused primarily by individual phases of voltage-controlled capacitors responding to PV and load fluctuations.

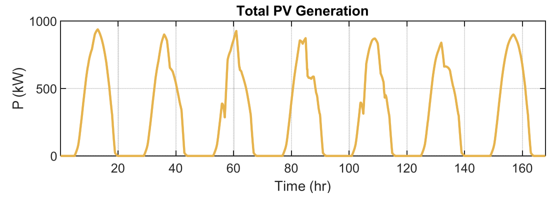

FIGURE 5. Total PV generation during simulated week.

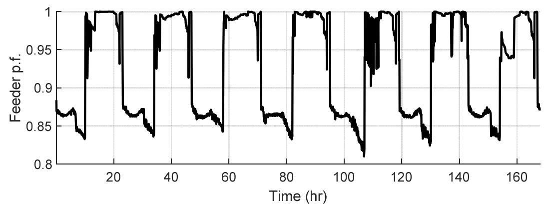

FIGURE 6. Baseline simulated feeder power factor without VB dispatch.

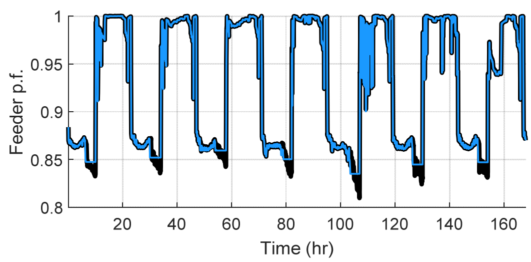

FIGURE 7. Optimal feeder power factor with water heater VB dispatch (blue) over simulated baseline feeder power factor without VB dispatch (black).

C. VB DISPATCH OF WATER HEATER FLEET

Given the baseline feeder power factor and the VB limits for the electric water heater fleet, the optimal VB profile was computed as described in Sections III-A and III-B. The optimal feeder power factor is shown in Fig. 7.

On each day, the minimum power factor was increased. The worst-case power factor day was the fifth day and the overall minimum power factor was increased by 0.025. The VB power and energy profiles are shown along with the VB power and energy limits in Fig. 8.

Because the electric water heater fleet VB has unity power factor, charging the VB (turning appliances on) improves the power factor of the system. Each day, the VB discharges in preparation to charge during the minimum power factor event; the VB discharges back to the neutral position after the event. The charging power limit is never approached and power factor improvement was limited by VB energy.

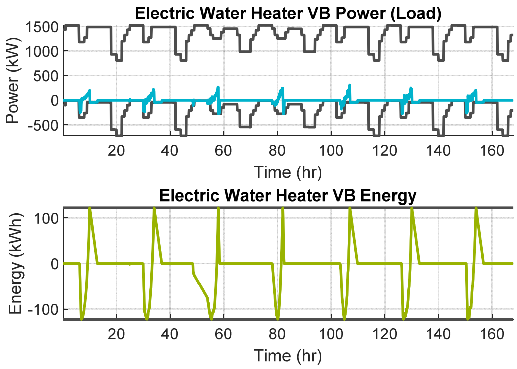

FIGURE 8. Water heater VB power profile (blue, top) and energy profile (green, bottom) for optimal dispatch; power and energy limits are shown in gray.

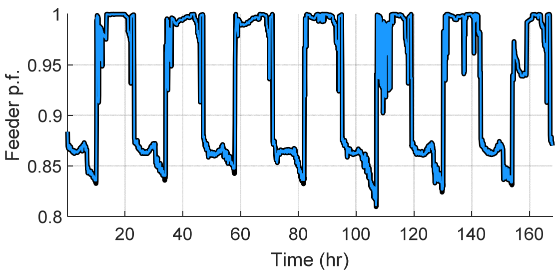

FIGURE 9. Optimal feeder power factor with air conditioner VB dispatch (blue) over simulated baseline feeder power factor without VB dispatch (black).

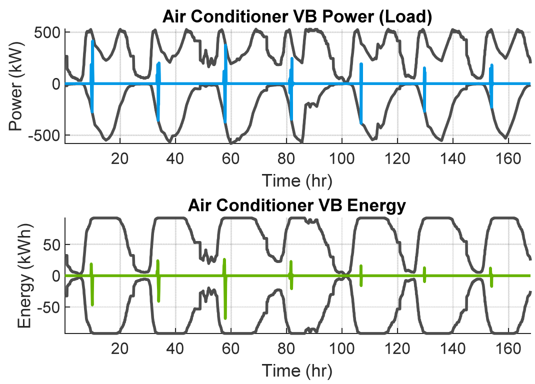

FIGURE 10. Air conditioner VB power profile (blue, top) and energy profile (green, bottom) for optimal dispatch; power and energy limits are shown in gray.

D. VB DISPATCH OF AIR CONDITIONER FLEET

Given the baseline feeder power factor and the VB limits for the air conditioner fleet, the optimal VB profile was computed as described in Sections III-A and III-B and the resulting power factor is shown in Fig. 9.

On each day, the minimum power factor was increased slightly. The worst-case power factor day was the fifth day and the overall minimum power factor was increased by 0.001. The VB power and energy profiles are shown along with the VB power and energy limits in Fig. 10.

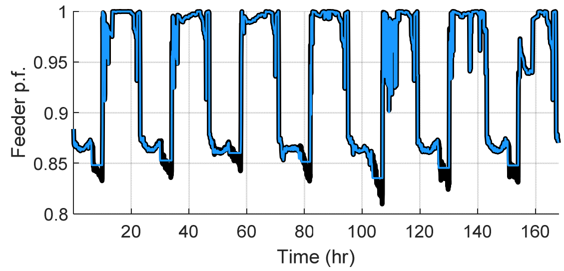

FIGURE 11. Optimal feeder power factor with air conditioner VB dispatch (blue) over simulated baseline feeder power factor without VB dispatch (black).

Because the air conditioner fleet in GridLAB-D has a power factor of 0.8 (as reflected in the VB model), discharging the VB (turning appliances off) improves the power factor of the system. Each day, the VB charges in preparation to discharge during the minimum power factor event. On each of the seven days simulated, power factor correction is limited by the VB discharging power limit and the VB energy limits are not reached.

E. JOINT DISPATCH OF COMBINED FLEET

The feeder power factor was optimized as described in Sections III-A and III-B considering both the water heater fleet VB and the air conditioner fleet VB. Joint optimization is described by (7)-(8). The optimal feeder power factor is shown in Fig. 11.

The power factor improvement is similar to that observed with the water heater VB only. The worst-case power factor day was the fifth day and the overall minimum power factor was increased by 0.026. The VB power and energy profiles for each VB are shown with their corresponding limits in Fig. 12.

The two VBs were jointly optimized. The power and energy profiles for the water heater VB are nearly identical to the water heater only case. However, the air conditioner VB was able to make a larger impact at the beginning and/or end of the minimum power factor event, extending the event and slightly increasing the minimum power factor compared to the water heater only case.

F. COMPARISON OF SCENARIOS

The feeder power factor and improvement for each of the scenarios discussed is summarized in Table I.

All VB dispatch scenarios showed positive improvement in feeder power factor across all days (also see Fig. 7, Fig. 9, and Fig. 11). The greatest improvement in the combined VB case came on the worst-case day. The worst-day feeder power factor improvement for each scenario is shown in Fig. 13.

The worst-day feeder power factor was improved in all VB dispatch scenarios. However, the improvement achieved with VB dispatch for electric water heaters is an order of magnitude greater than that achieved by VB dispatch of air

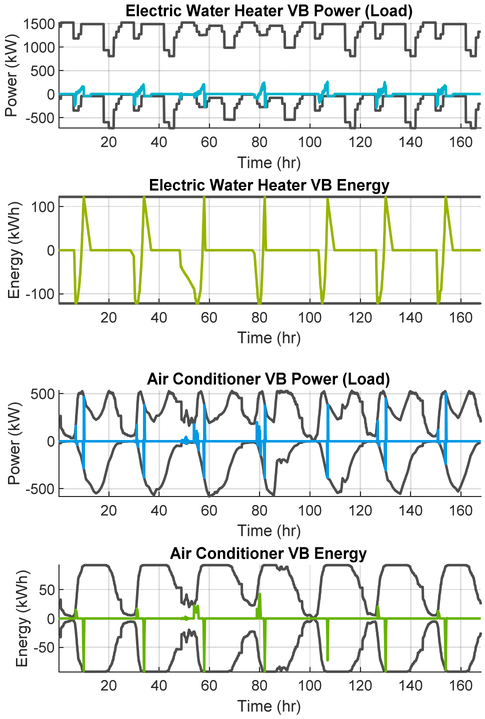

FIGURE 12. Water heater VB power profile (blue, first from top) and energy profile (green, second), and air conditioner VB power profile (blue, third) and energy profile (green, fourth) for optimal dispatch; power and energy limits are shown in gray.

TABLE 1. Feeder Power Factor and Change in Power Factor by Day

p.f.[a]	D1	D2	D3	D4	**D5**[c]	D6	D7
Base	0.833	0.836	0.842	0.832	**0.810**	0.824	0.831
WH[d]	0.848	0.852	0.859	0.850	**0.835**	0.845	0.847
AC[e]	0.836	0.840	0.847	0.836	**0.811**	0.826	0.834
All[f]	0.848	0.853	0.860	0.851	**0.835**	0.845	0.848
$\Delta p.f.$[b]	D1	D2	D3	D4	**D5**[c]	D6	D7
WH[d]	0.015	0.016	0.017	0.018	**0.025**	0.021	0.016
AC[e]	0.003	0.004	0.005	0.004	**0.001**	0.002	0.003
All[f]	0.016	0.017	0.018	0.019	**0.026**	0.021	0.017

[a]Daily feeder power factor daily minimum.
[b]Daily change in power factor with the introduction of VB dispatch.
[c]Overall weekly minimum p.f. and overall weekly improvement.
[d]Optimal VB dispatch for electric water heaters only.
[e]Optimal VB dispatch for air conditioners only.
[f]Optimal VB dispatch for the combination of both VBs.

conditioners. As on other days, most of the improvement came from the water heater VB.

V. CONCLUSIONS

The VB framework allows thermostatically controlled residential appliances to be controlled optimally. In order to implement this scheme, a centralized controller requires feeder load monitoring (substation SCADA), device characterization to build the VB profiles, and the ability to dispatch participating devices using a method such as priority stack control. This framework can be used to improve the power factor of distribution feeders, reducing transmission and distribution system losses.

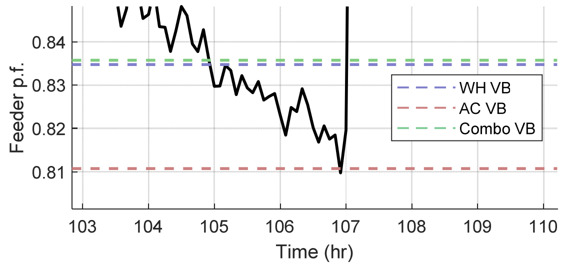

FIGURE 13. Lowest power factor event on day 5: baseline feeder power factor (black) and minimum power factor thresholds for each VB dispatch scenario.

Modeling and analysis suggest that on a particular western United States feeder with residential and commercial load, VBs consisting of electric water heaters from 100% of residences and air conditioners from 45% of residences could improve the daily minimum power factor by up to 0.026. Power factor improvement ranged from 0.016 to 0.026, with the greatest improvement coming on the worst-case day.

Considered individually, optimal VB dispatch of the electric water heater fleet improved the daily minimum power factor by 0.015 to 0.025 and optimal VB dispatch of the air conditioner fleet improved daily minimum power factor by 0.001 to 0.005. The unity power factor of the water heater fleet means that it has a greater effect on power factor per kilowatt dispatched. In addition, at the time of day that the minimum power factor occurs, the electric water heater VB has a higher power limit than the air conditioner VB in the direction that improves the feeder power factor (positive for the water heater VB and negative for the air conditioner VB) when the daily minimum feeder power factor occurs. The water heater VB was constrained by its energy limits while the air conditioner VB was constrained by its power limits.

The VB approach to power factor correction leverages resources that are already present on the system and does not require investment in a combination of infrastructure upgrades such as capacitors, voltage regulators, and line upgrades that might otherwise be required for power factor correction without introducing overvoltage violations. The communications and control infrastructure required for VB dispatch are comparable to and likely to be compatible with that required for load-aware VVO or transactive control.

Daily minimum power factor maximization does not require full utilization of VB resources so capacity remains available for other services. Other services could be provided either by co-optimal dispatch of the VB resource for power factor correction and other services or by considering VB resources and constraints as part of a state-aware VVO or other system-wide power-flow optimization. Future work will continue to investigate how the VB framework can be used to provide the best value to the power system considering both the transmission and distribution levels.

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ANDREW P. REIMAN (M'09) obtained his B.S. in Electrical Engineering from the University of Michigan and his M.S. and Ph.D. in Electrical Engineering from the University of Pittsburgh. Dr. Reiman is a research engineer at Pacific Northwest National Laboratory. He has over 9 years of experience in industry and research. His technical interests include distribution system modeling, simulation, and state estimation; distributed energy resource integration; and stochastic power system modeling.

ABHISHEK SOMANI has a Ph.D. in Economics from Iowa State University with specialization in the analysis of electric power systems. He presently works as a senior research economist at Pacific Northwest National Laboratory. Dr. Somani's research interests include electric power markets, both in the United States and internationally. He has analyzed the impacts of large-scale renewable penetration on power market outcomes.

M.J.E. ALAM (S'10–M'14) is a power systems engineer at Pacific Northwest National Laboratory. His research engagement encompasses projects on testing, demonstration, and evaluation of energy storage benefits for the power grid as well as projects in transactive energy systems and the grid services valuation domains. Before joining PNNL, he was engaged in solar PV and energy storage research in Australia and also worked for 5 years as an electric power industry professional in Bangladesh. Dr. Alam obtained a Ph.D. in Electrical Engineering from University of Wollongong, NSW, Australia in 2014, and B.S (2005) and M.S. (2009) degrees in Electrical and Electronic Engineering from Bangladesh University of Engineering and Technology, Dhaka, Bangladesh.

PENG WANG (M'17) is an engineer with Pacific Northwest National Laboratory. He received the Ph. D. degree in Electrical Engineering from the University of California, Riverside in 2017, the M.S. degree in Control Science and Engineering from Shanghai Jiao Tong University in 2013, and the B.S. degree in Mathematics from Shandong University in 2010. His recent research focuses on control an optimization of distributed energy resources and demand response.

DI WU (M'12–SM'17) received the B.S. and M.S. degrees in Electrical Engineering from Shanghai Jiao Tong University in 2003 and 2006, respectively, and the Ph.D. degree in electrical and computer engineering from Iowa State University, in 2012. He is currently a staff engineer with the Electricity Infrastructure and Buildings Division, Pacific Northwest National Laboratory. His research focuses on control and optimization of distributed energy resources and demand response, assessment of energy storage for grid applications, and building-to-grid integration. He is an associate editor for the IEEE Power and Energy Technology Systems Journal.

KARANJIT KALSI (M'10–SM'18) received the M.Eng. degree from the University of Sheffield, Sheffield, U.K. in 2006, and the Ph.D. degree in electrical and computer engineering from Purdue University in 2010. He is currently a principal engineer in the Optimization and Control Group with Pacific Northwest National Laboratory.