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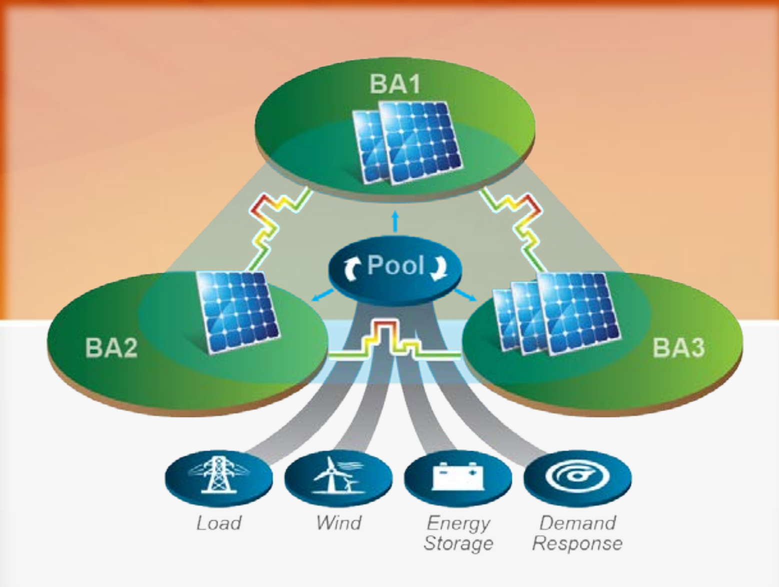

Solar-Centered Grid Project

Final Technical Report

February 2019

LE Miller
YV Makarov
MR Weimar
PV Etingov
A Somani

Prepared for the U.S. Department of Energy
under Contract DE-AC05-76RL01830

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Pacific Northwest National Laboratory
Richland, Washington 99352

Abstract

This report summarizes a study of pooling balancing area control metrics to reduce the impact of solar output variability. Sample data comes from the California Independent System Operator and the western Energy Interchange Market. Based on promising results obtained, the methodology was incorporated into an operational software tool, and a cost/benefit analysis of adopting the tool was used. The report also contains example analysis of five potential solar impact scenarios, including rates, system inertia, forecasting, market operations and community solar adoption.

Executive Summary

The Soft Cost (SC) program within the DOE EERE Solar Energy Technologies Office (SETO) supports efforts to make solar deployment faster, cheaper and easier. Soft costs include financing, customer acquisition, permitting, installation, labor, inspection, and other non-hardware costs. Taken together, soft costs and barriers to solar deployment now make up over half the total cost of solar generation. This project supported key SC activities aiming to harness big data, connect technical solutions to stakeholders, and support finance and business solutions that accelerate market growth and expansion.

The project was funded by the SC program through the SunShot National Laboratory Multi-year Partnership (SuNLaMP) program. It was undertaken to address perceived barriers to solar power integration, primarily resulting from its variability. The main hypothesis was that pooling variability in area control error (ACE) across multiple balancing areas (BA) would improve system control performance metrics. This hypothesis was tested by simulation on a year's worth of system data for the western Energy Interchange Market (EIM), which has some evolving aspects of a market-of-markets. The results of BA pooling were that ACE uncertainty reduced by 22% to 48%, depending on the hour of day and day of year. A software tool based on the methodology was implemented, and a cost/benefit analysis showed that its development cost would be recovered in less than a month. This conclusion is based on the California Independent System Operator's (CAISO) estimate of $2.1M savings per month, in reduced regulation reserve (RR) requirements.

Furthermore, based on the study period's data it was noted that wind ramps were more significant than solar ramps in determining RR. Load ramps and conventional generation uncertainty also contribute significantly to RR. The concept of a solar-centered grid means that all sources of variability are treated on a comparable basis, i.e., they are all part of normal grid conditions. This report includes five sample use case analyses of perceived integration barriers, namely rates, system inertia, forecasting, market operations and community solar. Those five use cases illustrate how perceived barriers can be managed in the solar-centered grid.

The report includes five main sections and two appendices:

- Section 1 summarizes new control metrics and operational challenges
- Section 2 presents the analysis of perceived barriers, i.e., five use cases
- Section 3 summarizes the main results in ACE variability reduction by pooling across BAs. It also presents a secondary observation, that wind ramps were more significant than solar ramps in determining higher RR requirements.
- Section 4 discusses cost/benefit analysis of operational methodologies, with some lessons learned about the importance of interdisciplinary teams (i.e., engineering and economics) and data sources.
- Section 5 summarizes the conclusions and recommendations
- Appendix A graphs a full yearly set of data to support Section 3.
- Appendix B contains a draft technical paper on data-handling methods, which may be extended and submitted to a future conference.

In addition, this work has produced two peer-reviewed conference papers (Etingov et. al. 2018, Weimar et. al. August 2018) and one published webinar (Weimar et. al. March 2018).

Recommendations for future work include tuning parameters of the existing methodology for operational deployment, and also exploring new machine learning approaches to improve the methodology.

Acknowledgments

The authors acknowledge the support and coordination provided by Ammar Qusaibaty and Elaine Ulrich of the U.S. Department of Energy Solar Energy Technologies Office. The authors are also grateful for the support and collaboration of Clyde Loutan and Amber Motley of CAISO, of PacifiCorp, and Ken Pennock of AWS Truepower. The authors also acknowledge our colleagues Tom McDermott, Frank Tuffner, and Nader Samaan at Pacific Northwest National Laboratory for their support, comments, and review of this work.

Acronyms and Abbreviations

ACE	Area Control Error
AGC	Automatic Generation Control
BA	Balancing Authority
BAL	NERC Reliability Standard
BAAL	Balancing Authority ACE Limit
CAISO	California Independent System Operator
CPS1	Control Performance Standard 1
CPS2	Control Performance Standard 2
DA	Day Ahead
DARP	Day Ahead Ramping Prediction Tool
DCS	Disturbance Control Standard
DG	Distributed Generation
EIM	Energy Interchange Market
FERC	Federal Energy Regulatory Commission
FTL	Frequency Trigger Limit
GTM	Greentech Media
IEEE	Institute of Electrical and Electronic Engineers
IPP	Independent Power Producer
L_{10}	The limit on average ACE for at least 90% of the 10-minute periods in a month
NERC	North American Electric Reliability Corporation
NO_X	Nitrogen Oxides
O&M	Operating and Maintenance Cost
PV	Photovoltaic Solar Generation
REC	Renewable Energy Credit
ROI	Return on Investment
RR	Regulation Reserves
SCADA	Supervisory Control and Data Acquisition
SO_X	Sulfur Oxides
WECC	Western Electricity Coordinating Council

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1.0 Introduction

The North American power grid is an example of single-machine physics operating on a continental scale. For most of its history, adequate system modeling, computational power, and measurement technology to operate the grid with an accurate understanding of its state and available margins did not exist. This is largely no longer true, but existing operational practices, regulation, and market rules were designed to keep the grid online with a great deal of information about its state and capacity unknown.

Because of these historical reasons and conventional practices, a key barrier to penetration of solar energy into the grid at high levels is lack of confidence on the part of system operators, planners, market designers, and regulators that the right information can be made available to maximize the potential of solar energy. This project attacks that barrier by showing how placing solar energy at the heart of how the grid is understood and operated makes it possible to make the right information available at the right time.

In existing operational practice, power grids are controlled by BAs. Each BA controls a certain part of the grid and is responsible for balancing its generation against its loads. BAs are also responsible for maintaining their energy interchange with neighboring BAs based on predetermined schedules and obeying power transfer limits on the connecting transmission lines as shown in Figure 1.1. Conventional power grid operational and control practices use the approximation that the various types of sources of energy in the system and the various types of energy sinks or loads are fundamentally deterministic and continuous in their behavior. This approximation underlies the basic models of how sources and loads behave. The models are then patched to account for ways in which various types of sources and loads do not quite fit the basic model, such as variability and uncertainty associated with solar generation.

The reality is that there is no type of load or source in the bulk power system that behaves in such a simplistic fashion. All types of resources contain some uncertainties, some non-deterministic behavior. For example, conventional forms of generation have an associated probabilistic failure-to-start, uninstructed deviations, and other complexities, which need to be accounted for. The properties of solar energy, including uncertainty and variability, represent the true base model for power systems operation.

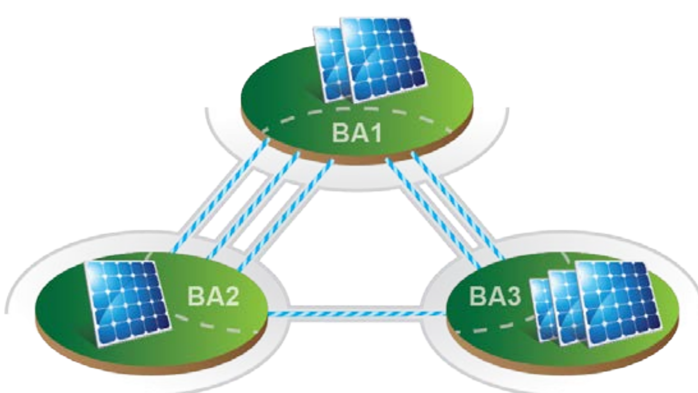

Figure 1-1: Conventional operating practices. Solar power is usually confined to local markets within the same BA. The balancing process is internal to each individual BA. Interchange flows between BAs are held to predetermined schedules.

Conventional power grid operating practice in the United States attempts to hold power interchanges constant across control area boundaries. Mutual agreements between control areas are made in advance as to what the interchange levels should be, and the areas are operated to hold those values as constant as possible. The values chosen are set well within the physical limitations of the transmission paths involved for reliability purposes.

The concept of a Solar Centered Grid incorporates solar power into the definition of what is “normal”, i.e., it’s treated on the same basis as uncertainties in all forms of generation.

Limiting the balancing and interchange processes and regulatory scores to individual control areas may form an unnecessary barrier to increased solar penetration. Taking advantage of the amalgamating and smoothing effect of the total output of variable generation over wider geographic areas is a major advantage of consolidating areas of control. Performing balancing control over a wider area alleviates some of the effects of any form of uncertainty in the system, from any type of load or source. It is not necessary to restrict the borders of a control area to the borders that limit the area over which balancing control is performed. It has been shown in practice that pooling balancing-control information from several control areas and distributing the total balancing job among those multiple areas reduces the total amount of balancing resources needed, and as a result allows for more solar generation in the system. Methods for assessing the unused capacity of those transmission paths in real time would allow that capacity to be put to use, if there were additional tools to allow that now-identified capacity to be traded on the markets.

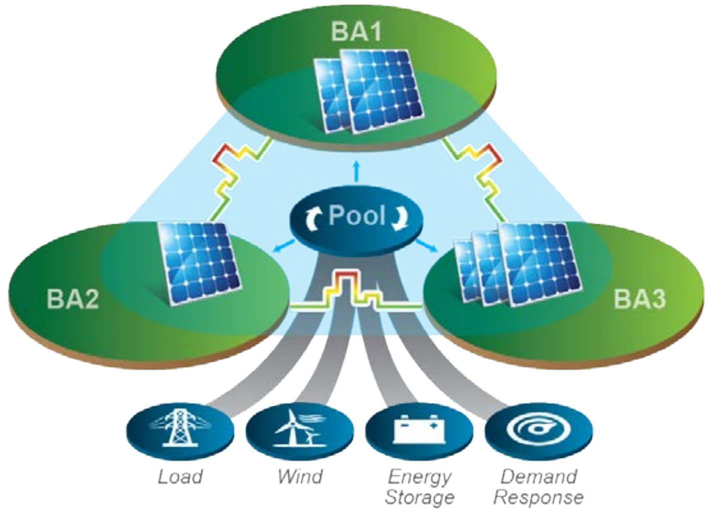

Figure 1-2: The solar-centered grid. Solar power and associated variability are pooled and sold where it is needed, within or across BA borders. Balancing control crosses BA boundaries. Interchange flows between BAs are dynamically managed to maximize use of capacity. This pool of energy resources and variability that can be traded can include all energy resources in the system, including wind, energy storage and demand response.

Our hypothesis is that balancing control can be performed across control area boundaries, as shown in Figure 1.2, by the use of dynamic "virtual" interchange methods, tools, and market rules. The testbed for this hypothesis was CAISO and the Energy Interchange Market, and we used probabilistic methods and metrics as summarized in (Makarov et. al. 2013).

1.1 Selection of Focus Area

The area of focus for testing this project is the Energy Imbalance Market (EIM), also known as the Western EIM, run by the California Independent System Operator (CAISO). The EIM involves a rudimentary market-of-markets structure across which solar variability (and eventual flexibility) could potentially be traded. The Energy Imbalance Market is expanding, as seen in Figure 1-3. Rather than create a separate energy imbalance market in the Pacific Northwest, entities in that area may converge on joining the EIM instead.

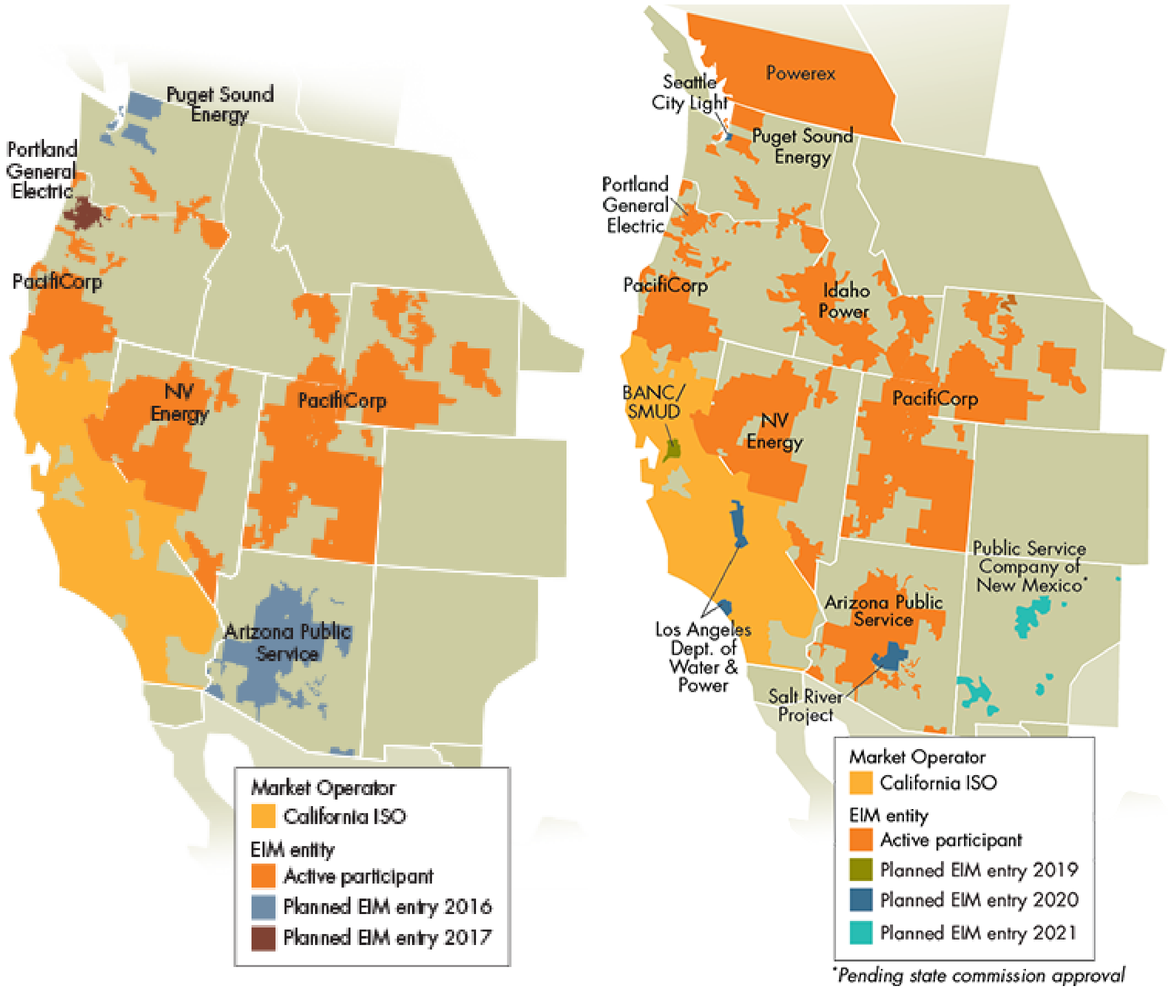

Figure 1-3: Growth of the EIM service territory from 2016 (left) to 2018 (right).

1.2 Evolving Challenges

As seen in Figure 1-4, solar and wind generation continue to grow rapidly in CAISO. Beginning in January 2016, extreme solar output swings caused CAISO to entirely run out of regulating capacity for 25-35 minutes at a time, which is very unusual. These events have continued. One conclusion is that CAISO should purchase more regulation as an ancillary service, but they didn't know at the time how much was reasonable to purchase. The markets are becoming faster, as CAISO changes from a 10-minute to a 5-minute real-time market interval in 2018. In 2020, CAISO plans to change the day-ahead market interval from 60 minutes to 15 minutes.

In addition, regulatory standards began to change as the NERC Balancing Authority ACE Limit (BAAL-003) standard became active on April 1, 2016. This rollout caused electricity industry entities to encounter unforeseen implicit barriers to high levels of solar penetration.

The standards and metrics currently applicable to CAISO include:

- **Control Performance Standard (CPS1) -** measures how well a BA's ACE performs in conjunction with the frequency error of the Interconnection, must be ≥ 100%

- **Balancing Authority Ace Limit (BAAL) -** is a real-time measure of area control error and system frequency, which cannot exceed predefined limits for more than 30-minutes

- **Disturbance Control Standard (DCS) -** is the responsibility of a BA to recover its ACE to zero if its ACE just prior to the disturbance was greater than zero or to its pre-disturbance level if ACE was less than zero within 15 minutes, must be equal to 100%

- **Frequency Response -** All BAs must support the interconnection frequency within 52 seconds following a disturbance greater than 500 MW anywhere within the interconnection

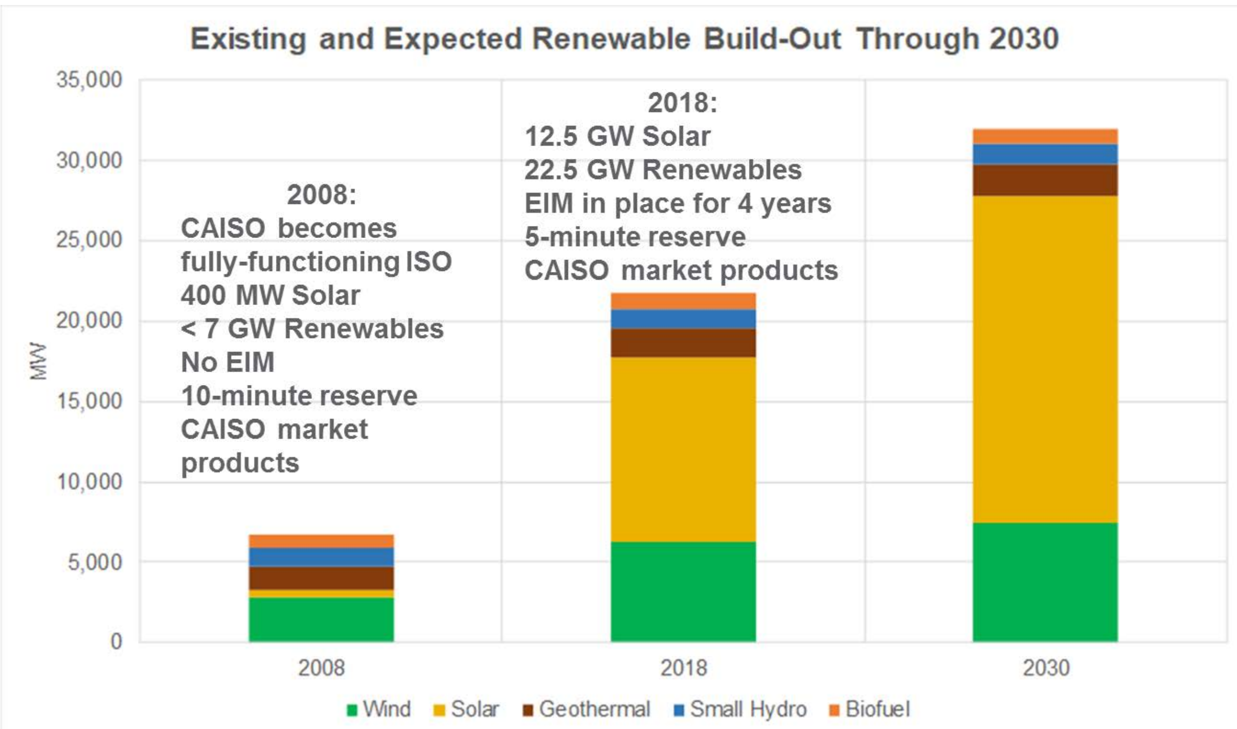

Figure 1-4: CAISO existing renewables through 2030 for 2008, and 2018, and expected renewables buildout by 2030. Modified from information provided by CAISO.

1.3 Balancing Authority ACE Limit

The Balancing Authority ACE Limit (BAAL) Standard has replaced the Control Performance Standard 2 (CPS2) since 2016 in North America. It establishes frequency-dependent ACE limits.

"The standard has been designed so that the BA ACE limits become frequency sensitive and can be used by the system operators as performance indicators in real time. The balancing authority can monitor its own performance against its BAAL target and take corrective actions before one of its BAAL limits is exceeded."[1]

The following important potential impacts of the BAAL standard on system operations can be foreseen:

[1] WECC White Paper on the Proposed NERC Balance Resources and Demand Standards, 2006.

- A control that opposes frequency deviation always improves area performance against the BAAL. This means that the new standard will not have potential problems with compliance if control of the regulating resources is based on the local frequency signals rather than AGC signals.

- Unlike the CPS2 standard formulated for 10-minute averages of ACE, the BAAL standard is formulated for instantaneous values of the area control error.

- The BAAL standard is expected to relax the area regulation needs and reduce the regulation burden on resources providing regulation service.

- BAAL limits depend on the current frequency, f, and can be calculated using (1).

$$BAAL(f) = -10B\frac{(f_{low} - 60)^2}{(f - 60)} \quad (1)$$

where B is a BA frequency bias (MW/0.1 Hz) and f_{low} is a low frequency trigger limit (Hz). For example, the CAISO's frequency bias is −485 MW/0.1 Hz. For the Western Interconnect, f_{low} = 59.932 Hz.

Figure 1.5 illustrates CAISO BAALs calculated using (1). L_{10} limits are also shown. The L_{10} limits are temporarily used to restrict BA interchange variations; this measure is a precaution taken until sufficient experience is gained with BAAL, or until a justified additional limit is applied to the BA's ACE.

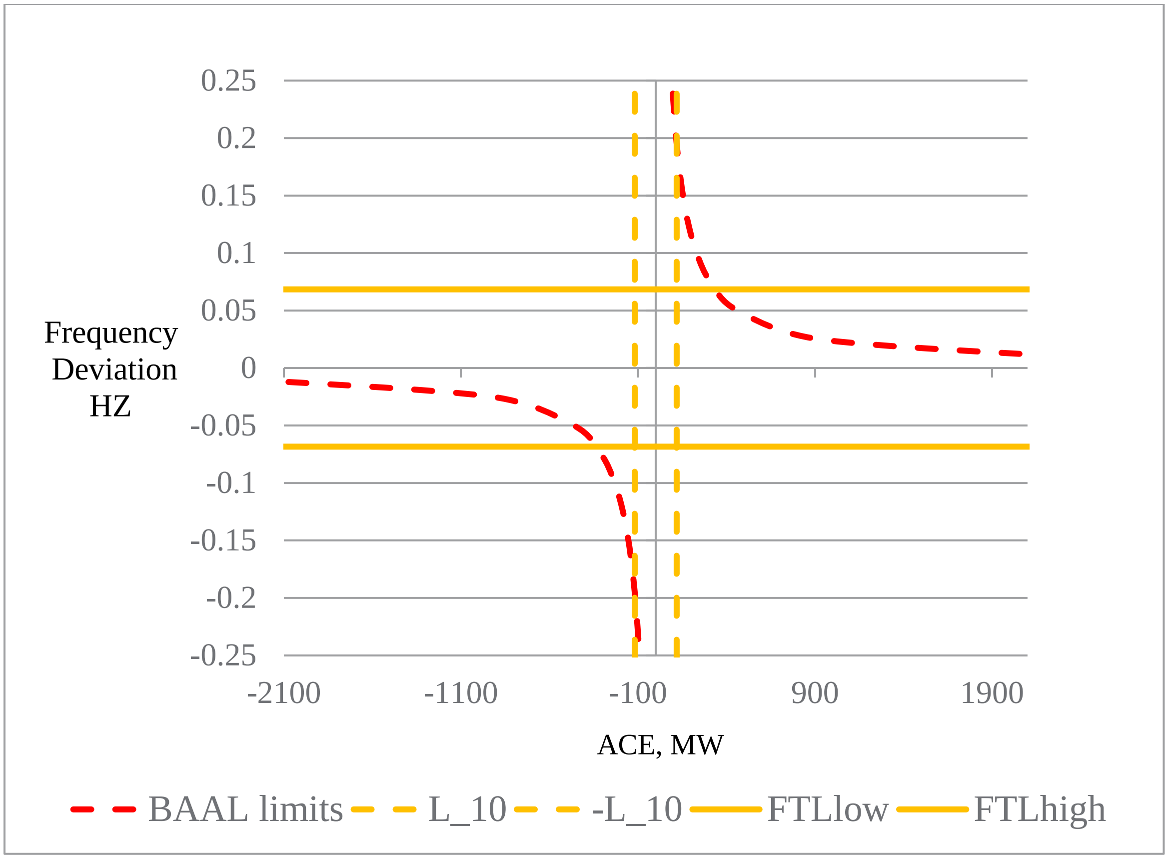

Figure 1-5: BAAL limits, L_{10}, and FTL_{low} and FTL_{high} plotted against frequency deviation as a function of ACE.

2.0 Barriers to Solar Penetration

PV penetration can impact stakeholders (customers, utilities, system operator, etc.) differently. Some stakeholders may be positively impacted, while others are negatively impacted, contemporaneously. Hence, to gain insights into the barriers to additional PV it is imperative to analyze the net results of impacts from all stakeholders' perspectives. This section presents five examples of possible barriers or other impacts from high PV penetration. Some of the interactions between impacts to different stakeholders will be identified, and the net result will be analyzed to assess whether it presents a barrier to additional PV. Figure 2-1 shows the overall framework of these interactions, which we analyze from several different viewpoints:

- Stakeholder – customer, utility, regulator, system operator, third-party
- Perspective – stakeholder view of specific set impacts
- Cost – stakeholder specific and overall costs (i.e., $, $/kW, $/kWh)
- Benefit – stakeholder specific and overall benefits (i.e., $, $/kW, $/kWh)
- Impact – stakeholder specific and overall power (kW), energy (kWh), etc.

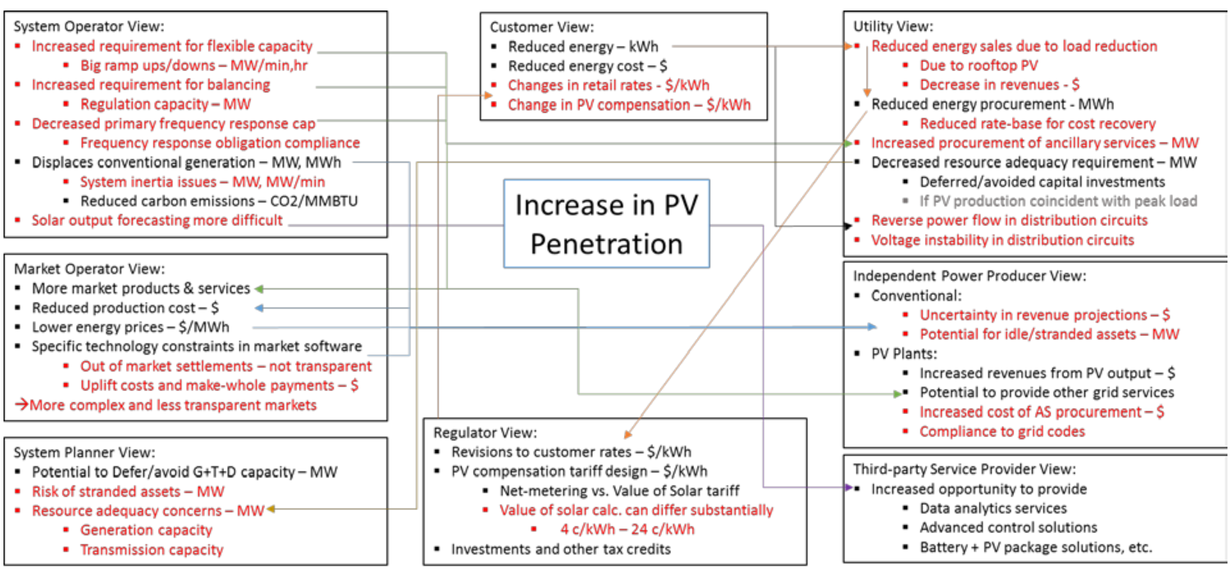

Figure 2-1: Example stakeholder impact and value interactions for increased PV penetration

2.1 Case 1: Rates

The adoption of rooftop PV was analyzed in (Cohen 2016), considering the customer, utility and regulator stakeholders. The effects of stakeholder impact interactions on the rates may be summarized as follows:

1. Customers reduce energy consumption and energy bill
2. Utility faces a reduction in retail energy sales and revenue. In turn, this reduces the rate base used to recover cost through the regulated returns on investments. Exacerbating this effect, costs may increase due to distribution system upgrades and shorter equipment lifetimes. On the other hand, the utility may reduce in wholesale energy procurement, which potentially reduces the need for operating reserves and other ancillary services, all of which would reduce cost.

3. Regulators probably have to conduct new rate case hearings to help utilities recover lost revenues. They may also consider net-metering vs. value-of-solar in these rate cases.
4. Customers may then see increased retail rates to help utilities recover lost revenues. This would impact ROI calculations, which may be seen as a potential barrier to PV adoption.

2.2 Case 2: System Inertia

A barrier to larger PV penetration is lack of system inertia provided by PV energy production. Under NERC regulation the System Operator must maintain power system balance and frequency. Lack of system inertia arises as PV penetration increases. At low levels of PV penetration, conventional generators can compensate for the lack of inertia through frequency controllers and then through governor action. But as PV penetration increases, the ability of conventional generators to compensate becomes more difficult. The system operator has at least five choices to solve the stability issue: 1) curtail PV production, 2) demand side management, 3) use energy storage if available, 4) call on flexible resources to provide regulation services, and 5) provide virtual or artificial inertia. All options have cost consequences. See Figure 2-2 for a graphical depiction of this use case analysis framework.

System Operator

For the System Operator as net load imbalance occurs the synchronous machines adjust to maintain balance. As PV penetration increases, the ability of synchronous machines to compensate decreases. The system operator keeps the system in balance by dispatching in real time flexible capacity to bring the system back in balance. In rare events when reserve capacity isn't available, an inability to meet frequency can lead to load shedding and customers experience outages. Under- and over-frequency can also damage customer's equipment (Rahmann and Castillo 2014).

Most PV with no inertia injects power only, which affects the electromechanical modes of other synchronous machines. Generators near PV injections can be adversely affected if their synchronizing capability is reduced (Vital 2011). Most legacy inverters currently deployed can't provide inertia but new smart inverters overcome this issue. Even with new smart inverters, they may not be used if there is no market for service or regulations don't require them. A market for artificial inertia and replacement of old inverters will reduce the problem. A positive benefit of PV penetration is displacement of fossil fuel generation, which decreases carbon emissions, NO_x, and SO_x emissions.

Market Operator

The Market Operator sees two upsides and a downside to increased PV electricity production. The first upside includes lower production costs because as PV enters, unit commitment models at a near zero marginal cost replaces more expensive marginal cost assets such as coal and natural gas gen-sets. The second upside is increased DG PV penetration displaces the most expensive generators in a net demand model decreasing the amount of conventional generation, thus reducing the overall price for electricity in both the day ahead and real time markets. The overall impact lowers energy prices. The downside is that out of market settlements occur and they are not transparent because they aren't seen in market transactions. The non-transparent costs include uplift costs and make-whole payments, which results in a more complex and less transparent market to ensure that the total costs of production are met. These payments are not made through a market, so they are not seen by all market participants. Over time the uplift payments need to make a gen-set owner whole, or the entity will go out of business.

Utility

The Utility faces added costs for providing advanced controllers to provide synthetic inertia. The costs of the controllers are increased costs for maintaining distribution system frequency and voltage.

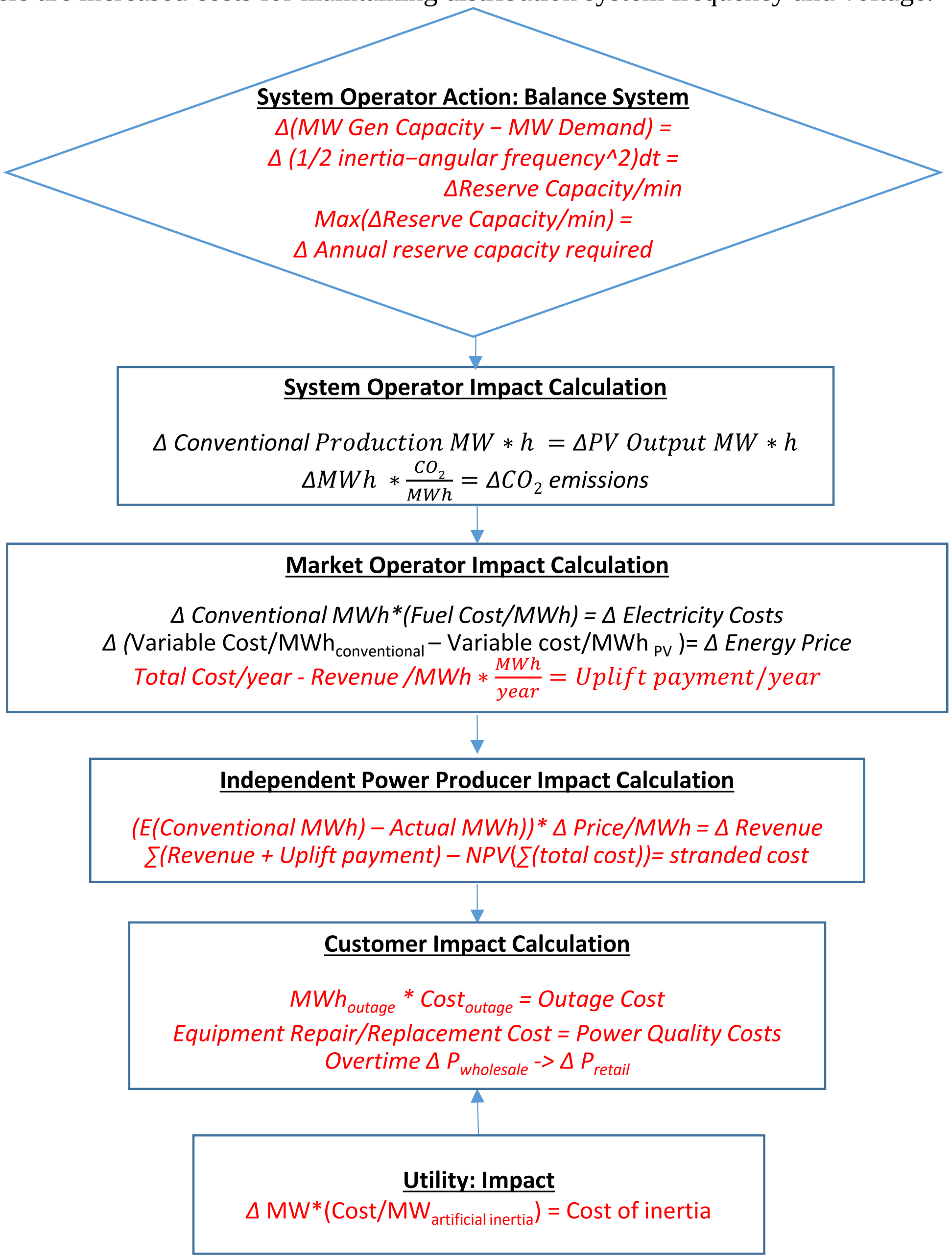

Figure 2-2: The economics behind the loss of inertia associated with increasing PV penetration

Independent Power Producers

The Independent Power Producer with conventional power sees a downside to the additional PV penetration. The conventional producer may find that as wholesale prices decline his unit may not be least cost-enough to enter the energy market or ancillary service market to earn sufficient returns on the asset. They are faced with more variable revenue because they don’t know how much revenue they will be receiving due to increasing solar penetration and the variability of solar output. In unit commitment models dispatch is based on the least cost units being used first and the market clearing price declines based on lower net demand. They also potentially see idle/stranded (equipment that isn't receiving compensation) assets, which can significantly reduce expected returns.

Customers

The Customer can experience power quality issues or outages with increased PV penetration. Higher penetration of PV provides technical concerns to customers because of the potential for outages in the most severe cases and grid stability, voltage regulation, and power quality defined as over/under voltage, flicker and frequency fluctuations in less severe cases. The latter power quality problems can result in damage to consumer's equipment, as well as to the transmission and distribution equipment (Bank et al 2013). Customers will see lower prices over time as regulators update their tariff schedules, but they may face increased costs due to utility controller and transformer upgrades.

2.3 Case 3: Forecasts

System Operator

The System Operator's grid stability requirements become more difficult to maintain as PV increase. Solar output forecasting is more difficult at the wholesale level and is exacerbated at the net demand level by increasing penetration of roof-top solar, which reduces net demand and makes forecasting capacity requirements more difficult at wholesale. The inability to forecast accurately the amount of solar output requires the system operator to purchase more ancillary services than may otherwise be purchased to ensure that the grid stays within system constraints (Ela et al 2013). That in turn increases operating costs because system operators must prepare for the worst outcome rather than for forecasted supply and demand. Figure 2-3 depicts the stakeholders and impacts of the increased penetration of PV, while Figure 2-4 graphically depicts the analysis framework.

Market Operator

Currently some wholesale markets are not capable of using batteries for ancillary services. FERC is in the process of rulemaking to amend its regulations under the Federal Power Act to remove barriers to the participation of electric storage resources and distributed energy aggregations in capacity, energy and ancillary service markets (FERC 2016). The market operator needs to establish participation models for electric storage and distributed generation resources. Market rules need to be developed.

Third Party Service Providers

Third-party service providers will find new opportunities to provide new data analytic tools, advanced control systems and battery plus PV packages. Data analytics services in the form of better forecasting of output and net load tools can improve solar forecasting and reduce the issues. In addition, data analytics tools that understand grid's state to understand system imbalances and correction need to be developed (Fusco et al 2016).

Advanced control solutions are required if voltage or frequency move outside set of bounds. The bounds for frequency and voltage are set by IEEE Standard 1547-2018. Outside these bounds, the PV system must disconnect (Yang et al 2014). There are some issues with controllers not correctly calculating frequency and causing faults, which provides opportunities for further for investment.
Battery plus PV package solutions are needed to allow the solar producer to provide more flexible solar output that can store output for arbitration and ancillary services. Advancements are still needed to lower the cost of storage solutions. Advancements require new chemistries to maintain power and depth of

discharge while lowering costs. Lower cost technologies have performance issues. Lithium ion has battery safety issues, e.g., fire. Also, lithium ion life has time limits (Whitacre 2016). Energy arbitrage prices in CAISO's day ahead and real time markets aren't feasible for PG&E batteries. Frequency regulation provided the best return in the CAISO markets, better than energy prices in the day ahead or real time markets. (Penna 2016).

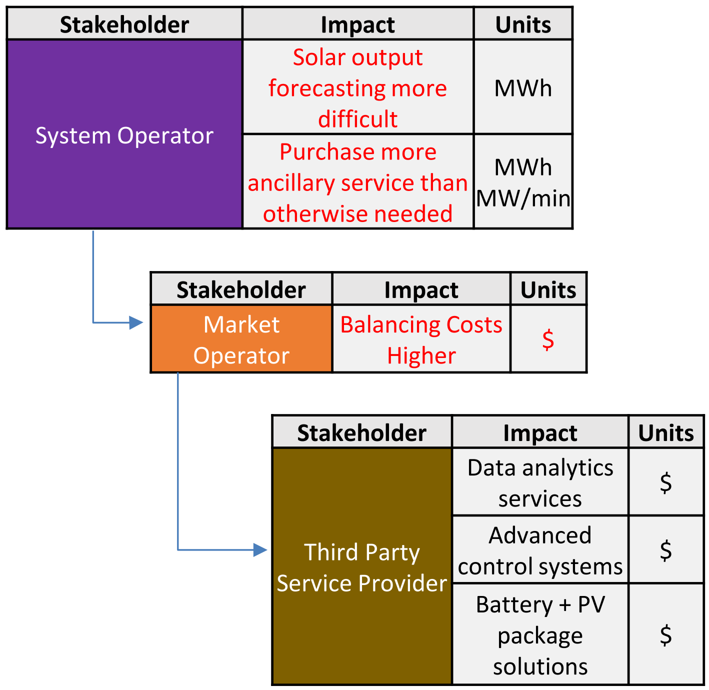

Figure 2-3: Poor PV forecasting increases the cost of electricity delivery

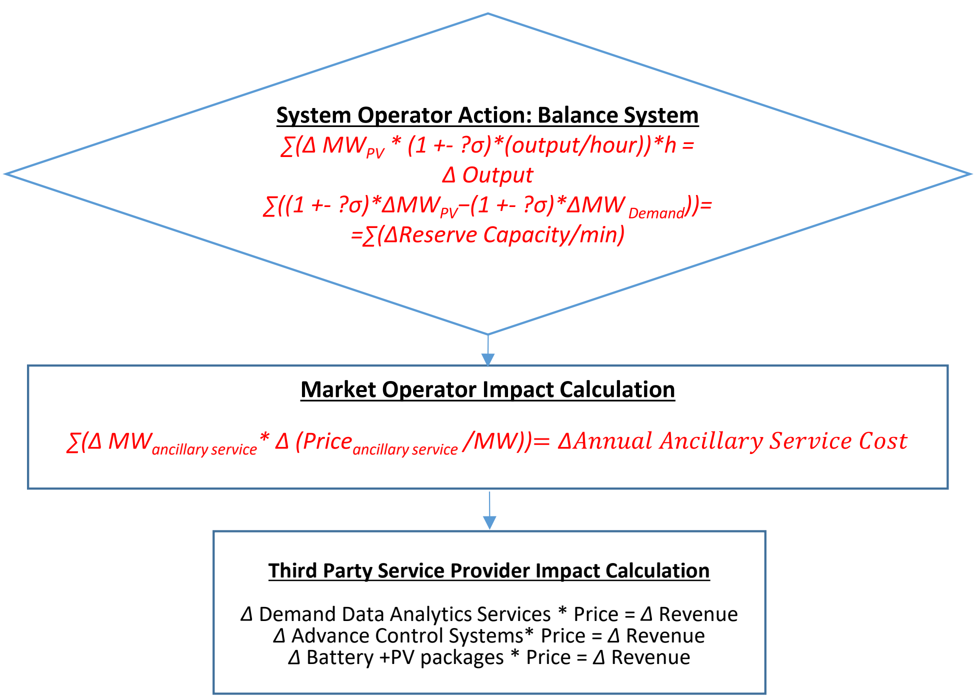

Figure 2-4: The economics of poor PV forecasting

2.4 Case 4: Market Operation

The wholesale market operator provides economic dispatch using unit commitment models, which dispatch lowest marginal cost energy first, following up the marginal cost curve to meet real time demand. Figure 2-5 shows the stakeholders and impacts, while Figure 2-6 depicts the analysis framework for this use case.

Market Operator

The market operator's current pricing mechanisms in wholesale markets are not conducive for solar penetration. Marginal cost pricing in economic dispatch models do not provide for full cost recovery of solar resources for zero to low marginal cost solar. For conventional generators, the marginal cost plus periods of significant demand imbalances allows most conventional units to breakeven in the long run. For solar, the marginal costs are below their long-run total costs. They are faced with negative prices during high production periods with lower than peak demand and during peak demand periods, their production is ebbing toward zero. Thus, they have little opportunity to reach their long-run total costs over time. This is called the revenue sufficiency or missing money problem (Newberry, 2015).

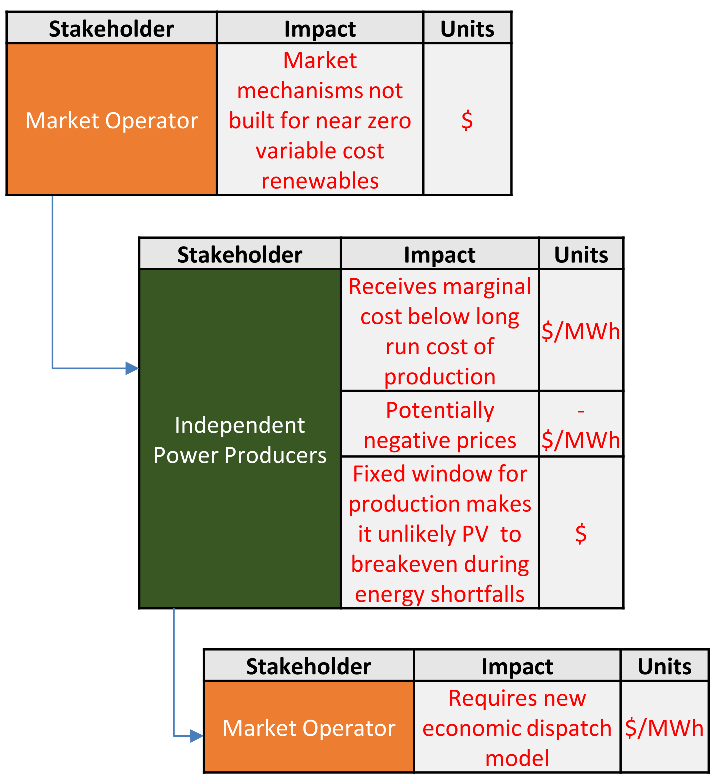

Figure 2-5: Conventional economic dispatch structures slow PV penetration

Independent Power Producer

The IPP PV energy producer sells energy into wholesale market if it doesn't have power purchase agreements. They receive wholesale prices that reflect the marginal cost of the most expensive conventional producers, negative prices during periods of oversupply and high prices during undersupply of energy if they have production. However, solar production is fixed to a window each day, making the likelihood that they can produce during periods where prices are high enough to offset negative prices and the lower than full costs of production associated with other periods. With increasing penetration, wholesale prices are lowest during PV's highest production period during the mid-day, which exacerbates the revenue sufficiency issue (except when wind production outpaced demand). Thus, price structures need to be revisited by Market Operators to develop price structures more conducive to solar.

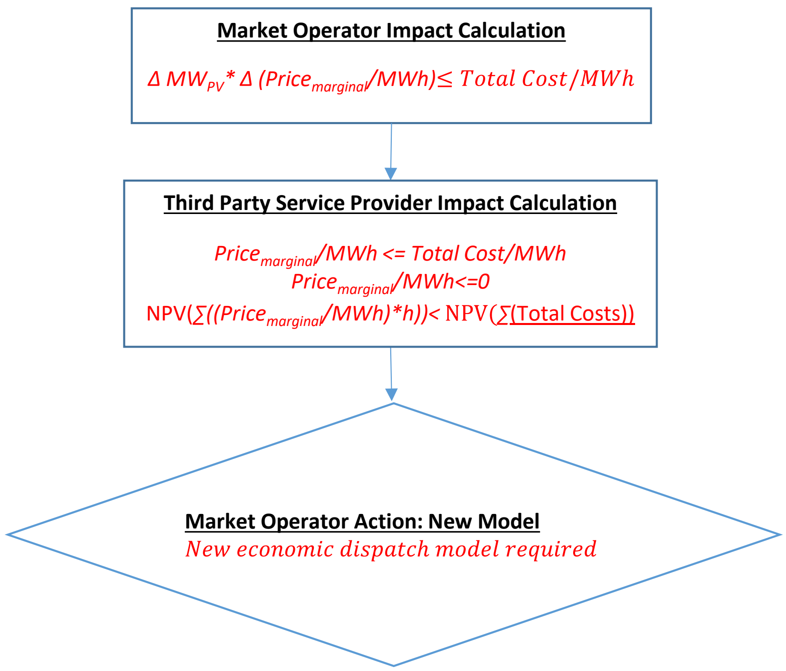

Figure 2-6: Assessment of new economic dispatch structures for solar

2.5 Case 5: Community Solar

Acceptance of Community Solar and lowering the barriers could allow for significant expansion of solar due to lower installed costs of capital and the larger market for community solar as compared with roof-top solar. When roof-top expansion of PV can't be accommodated, Community Solar offers the opportunity for customers to acquire solar energy. When solar customers can't afford the investment in solar or their rooftops can't accommodate solar, Community Solar provides an alternative that is lower cost per kWh than rooftop PV because it is installed at a larger scale. In addition, Community Solar can be placed such that it lowers congestion costs while reducing customers' bills.

The primary barriers to expanded Community Solar are legislative, regulatory, and business structures that can't absorb incentives as efficiently as other methods of solar production. Without legislation, community solar can't exist without utility approval either through virtual interconnection or utility-owned solar. Once legislation is in place regulations need to be developed to allow community solar. Once legal and regulatory hurdles are overcome, tax incentives may not have been structured to allow access by community solar. So even though the construction and operation of Community Solar should be less costly than roof-top solar, the net cost after incentives may not be lower.

There are three approaches to developing community Solar: utility, 3rd party and started by third party but dependent on legislation or utilities. Progressive utilities can build Community Solar without legislation as long as the tariff supporting the Community Solar is approved by the regulator. 3rd Party led solar already has legislative approval or will require legislation (Augustine 2015). Currently 16 states have legislation providing for Community Solar: California, Colorado, Minnesota, Wisconsin, New York, Connecticut, Rhode Island, Maryland, Maine, Vermont, New Hampshire, Massachusetts and Pennsylvania (Farrell 2015). Oregon has implemented legislation and Hawaii is debating Community Solar (K&L Gates 2016; Trabish 2016). Figure 2-7 and Figure 2-8 provide high-level summaries of requirements and impacts of Community Solar.

Stakeholder	Impact	Units
Legislature	Legislation allowing Community Solar	N/A

Stakeholder	Impact	Units
Regulator	Rate-case Hearings from Utility to Recover Lost Revenues & Additional Investments	N/A
	Rate Cases for Utility PV tariff	N/A
	Limits on Amount of Net Metered DG	N/A
	Implement Regulations to allow virtual net metering	N/A

Stakeholder	Impact	Units
Utility	Costs for artificial inertia	$/MWh
	Lower O&M if Utility Installed	$/MWh
	Requires Careful Structuring	N/A
	Investment Tax Credit Amortized Over Life of PV	$/MWh
	Can Be Placed to Reduce Congestion	$/MWh
	Decreased Revenue	$

Stakeholder	Impact	Units
Third Party	Tax Incentives Not Developed for Community Solar	N/A
	Larger Market than Roof-top Solar	N/A
	Utility-scale Solar Less Costly than Roof-top	$/MW
	Unproven Financial Approach	N/A
	More Complex Business Process than IPP	N/A
	Securities Laws Limit Number of Participants	N/A

Stakeholder	Impact	Units
Customer	Upfront Investment Costs Lower	$
	Added Costs Due to Utility Upgrades	$/kWh
	Investment can be sold	N/A
	Lower Energy Bills	$

Figure 2-7: Community Solar expansion impacts

Legislature

State Legislatures may pass legislation that allows development of Community Solar. Utilities may or may not need legislation in order to undertake community solar depending on their state regulatory structure. Where legislation has deregulated investor-owned utilities to allow open markets for energy, Community Solar can be developed and sold to competitive retail suppliers and then marketing the product as a credit on the customer's bill (GTM 2017).

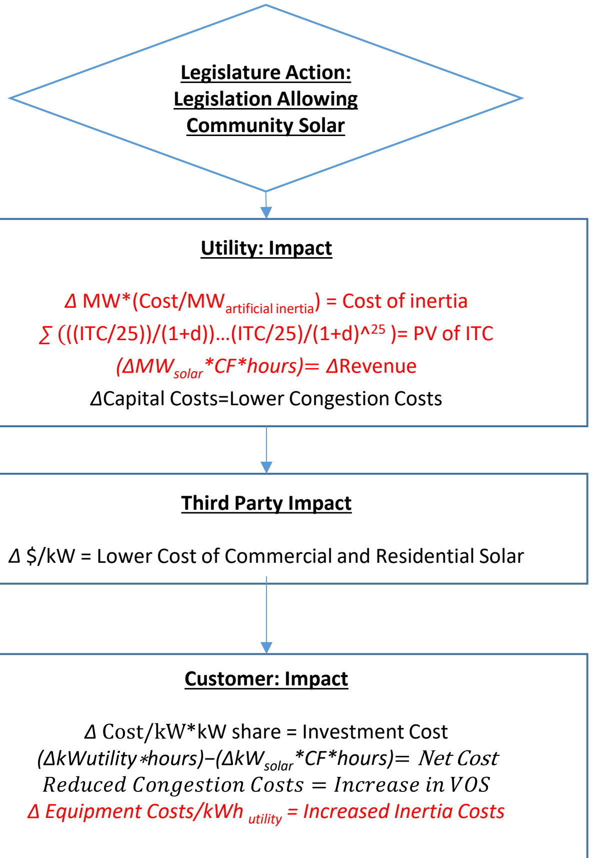

Figure 2-8: Analysis framework for Community Solar

Regulator

The regulator could build regulations based on the legislation to implement Community Solar by allowing virtual net metering. They also may determine the limits on the amount of net metered DG based on impacts to distribution grid stability. In addition, they may need to implement rate cases where needed to compensate utilities for lost revenue.

A barrier to Community Solar that may be addressed by Regulators is the level of net metering that is allowed. Utilities may set the net metering at very conservative rates to assure that solar production on Sunday noon is not greater than demand. That approach is often a conservative estimate. One study indicated that the amount of net metering could be double that of the conservative estimate if actual measurements of minimum load during daylight hours were done (Farrell 2012; Farrell 2013).

Utility

The utility may play two roles in Community Solar. The first would be as an implementer of Community Solar and the second as a responder to maintain grid stability as Community Solar is installed. In either case, the utility must accommodate the added solar. If the utility places the solar, they can place the solar where it relieves distribution system congestion best, which in the long run can reduce capital costs as line or substation reinforcement may not need to occur as quickly. However, the cost of artificial inertia will still be required in either case.

The main barrier to the utility in the case of accommodating 3rd party solar is the ever-increasing rate that utilities must face as more net metered solar is installed. The tariff rates increase as utilities must recoup lost revenues from net metered solar. For utility-driven community solar, customers pay more for the solar energy than they would in 3rd Party developed solar assuming they wouldn't invest in Community Solar unless the cost/kWh was less than the retail rate. An advantage is that Community Solar O&M is lower than traditional forms of generation, so the average cost of O&M to the utility will be lower.

Currently another barrier to utility installed Community Solar is that the utility must take care in structuring the project to keep the RECs and the benefits to themselves. Otherwise, the project could become subject to the securities rules. In addition, investment tax credits can't flow down to customers. In addition, municipal and cooperative utilities can't take advantage of the tax credits (Coughlin 2010).

Third Party Developer

The 3rd Party Developer of Community Solar faces many barriers in reaching a project deal. The primary barrier for developers is that not many MWs of capacity have been completed even though community solar has been around since before 2010. GTM (2017) indicated that total installed community solar was only around 343 MW in 2016 and that developing a project today was as complicated as it was three years ago indicating that barriers to project development haven't decreased. Project development, determining how to get credited for solar; and interconnecting to the grid are difficult aspects of Community Solar and each issue differs state by state where legislation allows.

Developing the project is more complex than utility scale IPP projects because more individuals need to be coordinated and brought under contract than under the IPP project. Usually, Community Solar looks for one large anchor customer and fills in the remaining customers from the commercial and residential sector. Another difficulty is that contracted customers usually need a credit score of 680 or better or the project can't get financed. Because the term of financing is usually 20-25 years and the asset itself is fungible, the developer needs backup customers if someone moves and opts out of the contract. It would seem that because of the high credit scores, financing would be simple, but it is not. Because so few deals have been done, the institutional investors and commercial banks don't have data to determine default rates, thus making them slow to finance.

Tax structures and incentives were developed for commercial and residential customers, thus structuring projects so that customers and the third-party developer can take advantage of them is difficult. For example, if the customer is a passive investor, (meaning that they have nothing to do with management or operations of the PV system) they can only offset tax credits against their passive income, which often is not enough to take advantage of the credits (Farrell, 2013; Coughlin 2010).

Customer

The primary barrier to customers in community solar is added costs associated with utilities providing artificial inertia to keep the distribution grid stable. Another barrier that can occur is that Community Solar can receive a substantially lower payment in comparison with rooftop solar, which is not offset by the lower cost of solar PV production. Thus, Community Solar can be less cost effective than rooftop solar. For example, Washington DC provides a net price of 8¢/kWh for Community Solar versus 13¢/kWh for rooftop (Delman 2015.)

There are a number of advantages compared with rooftop PV. The upfront costs can be lower because of the economies of scale associated with utility or commercial scale PV installation costs. In addition, the asset is fungible. If the Community Solar owner wished to sell their portion, the asset is fungible. Lastly, because of the virtual net metering nature, Community Solar reduces the total cost of electricity on a monthly basis.

3.0 Pooling Solar Variability across Boundaries

In existing operational practice, BAs are responsible for maintaining their energy interchange with neighboring BAs based on predetermined schedules, frequency support and obeying power transfer limits on the connecting transmission lines. Addressing solar variability is intended to be the separate responsibility of each BA as shown in Figure 1-1.

The reality is that a BA with a sufficiently high penetration of solar energy may find itself "leaning on the ties" during certain times of day, placing a burden to manage against its deviations and over-generation on its neighbors. How this impacts the BAs in question is complex since the applicable regulatory requirements are written to assume that this would not be normal practice.

The study reported in this section used data from three BAs of disparate size and generating portfolios to experiment with schemes for sharing responsibility for the total ACE diversity they experience between them, by postulating a hypothetical combined BA and seeking a sharing scheme for redistributing the burden of managing ACE variability among the participants in a way that would be of benefit to all participants.

Taking advantage of the amalgamating and smoothing effect of the total output of variable generation over wider geographic areas, along with different profiles of generating fleet flexibility, is a major advantage of consolidating areas of control. Performing balancing control over a wider area alleviates some of the effects of any form of uncertainty in the system, from any type of load or source. It has been shown in practice that pooling balancing-control information from several control areas and distributing the total balancing job among those multiple areas reduces the total amount of balancing resources needed, and as a result allows for more solar generation in the system.

The amalgamating of solar resources alone cannot reduce the solar ramping requirements during sunrise and sunset hours in BAs. Nevertheless, they can be partially addressed by using collective load profiles, correction to generation dispatches and using demand response and energy storage in the pool. As the last resort, solar ramp reductions of curtailments can be minimized in the pool in a coordinated fashion. Figure 1.2 implies also that the tie line schedules within a pool can be relaxed to extract more flexibility from the system.

3.1 ACE Diversity Sharing

ACE is an important system performance parameter used in CPS1 and BAAL reliability standards. ACE can be minimized by pooling diversity between BAs. Figure 3-1 through Figure 3-4 shows that pooling can reduce the uncertainty by 22% to 48%, depending on the hour of the day and the day of the year. No case was found in which pooling increased ACE. See Appendix A for more examples.

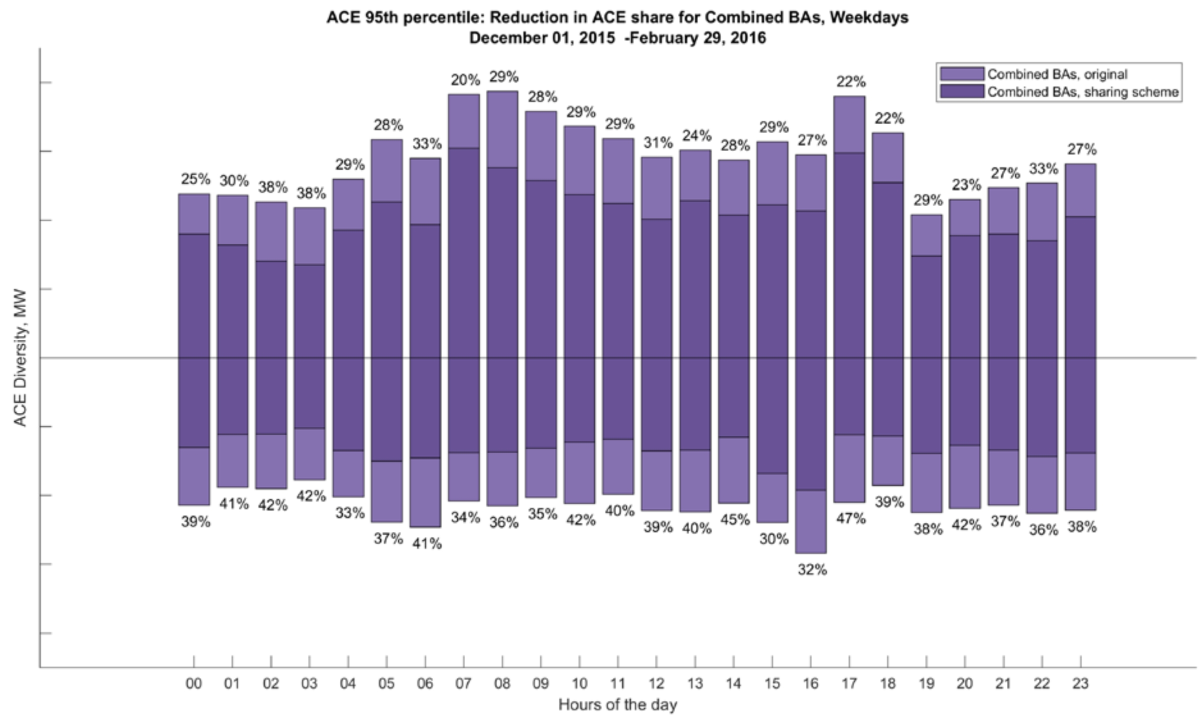

Figure 3-1: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in December 2015-February 2016.

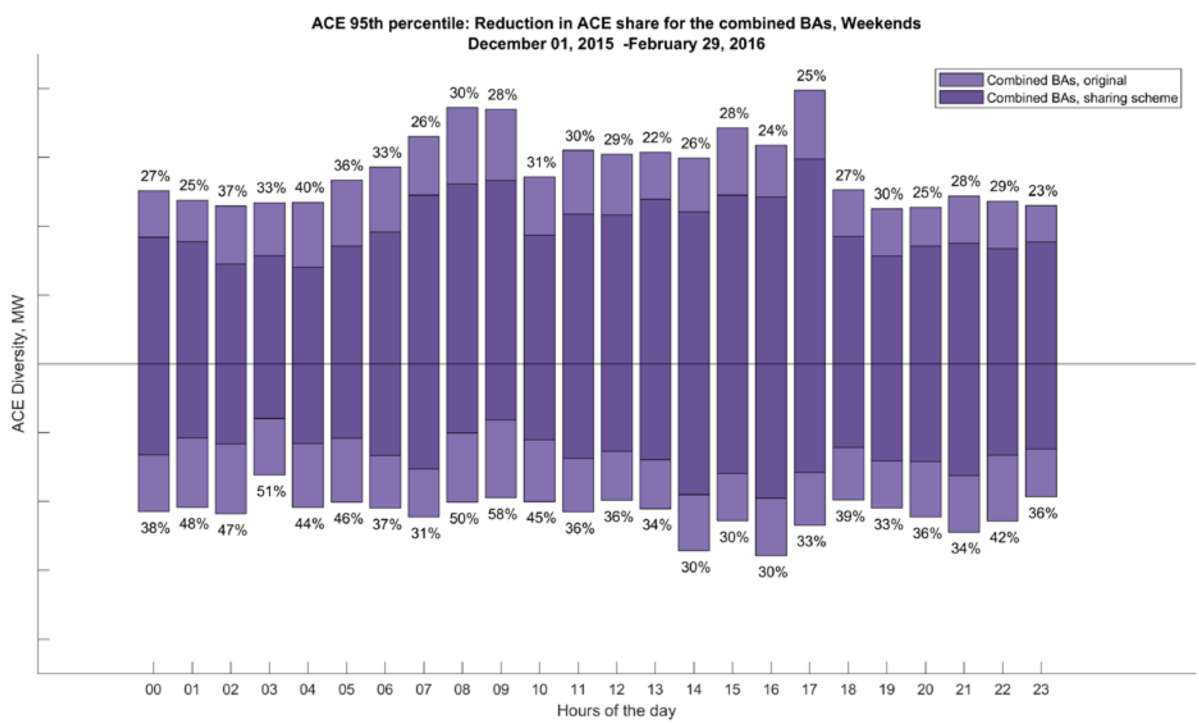

Figure 3-2: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekends in December 2015-February 2016.

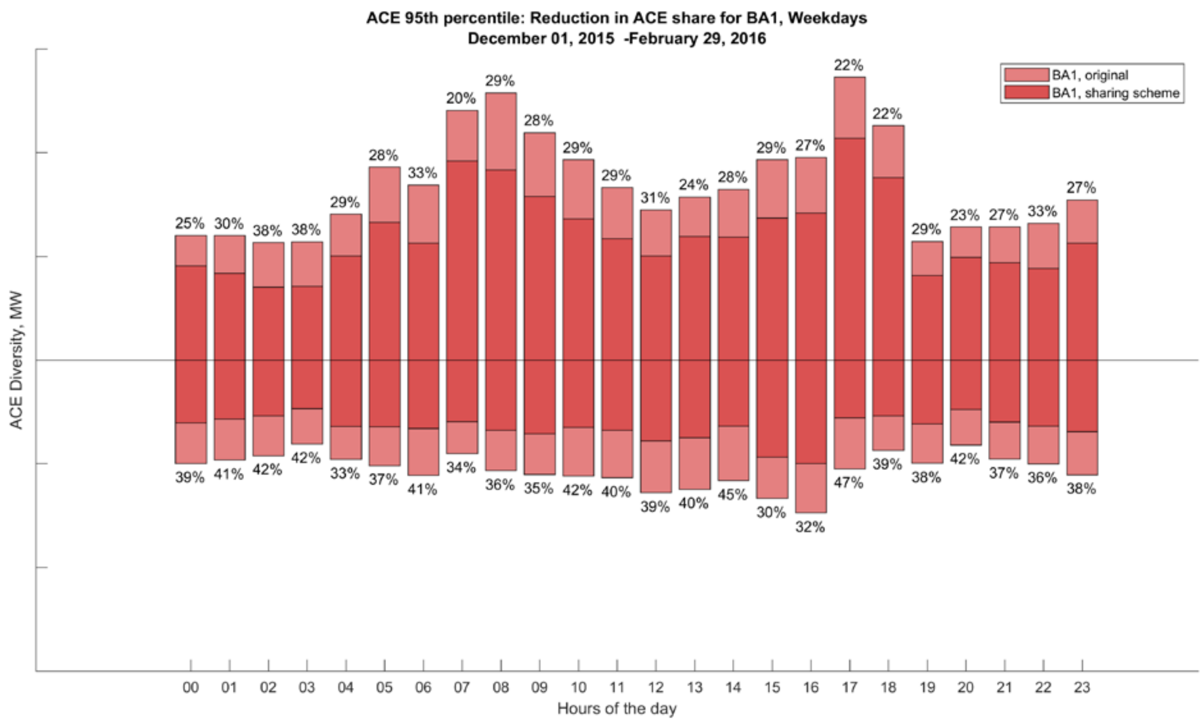

Figure 3-3: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in December 2015 - February 2016.

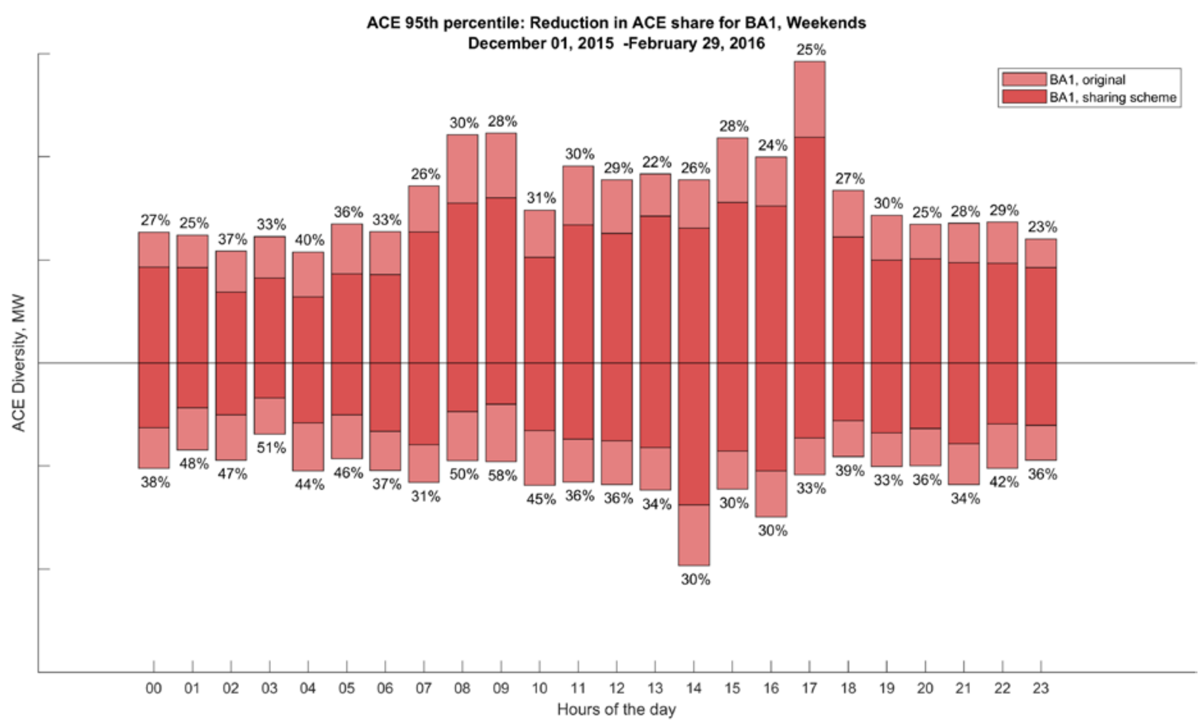

Figure 3-4: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekends in December 2015 - February 2016.

3.2 Uncertainty Reduction for Operational Control of Solar Swings

Starting in January 2016, days in which wide and fast-moving solar swings for the total CAISO service territory began to cause control performance issues for CAISO operations. The swings in question moved fast enough so as to be effectively invisible to the market runs and unit commitment and economic dispatch. Days in which this happened have continued since that time, increasing in both frequency and severity in the resulting control performance impacts.

Preliminary studies using time-series based uncertainty reduction methods to determine whether enough predictability of system frequency could be gained in that timeframe to be useful as the basis for some kind of additional operational control methodology.

The study initially looked at uncertainty reduction for frequency deviations only, which by itself is a fairly complex problem, because system frequency is comprised of many signals that operate at very different time scales. Initial runs tried to look ahead twenty minutes to one hour or more, to get an initial sense of what the method could do with frequency deviation input data. Then, since the CAISO market runs with the unit commitment and economic dispatch were running every ten minutes, runs focused on look-ahead windows in the 5-minute to 10-minute timeframes. It was uncertain whether enough dominance of the right components could be isolated to reduce uncertainty to any significant amount in a timeframe of less than ten minutes.

Initial results are summarized in Table 3.1. The study was then expanded to include more data and to refine the approach, and the results are discussed in the paper submitted to the IEEE Power and Energy Society General Meeting (see Appendix B).

Table 3.1: Reduction of uncertainty for system frequency deviations from 60 Hz.

date of data	**Data Resolution**	**Training period**	**Percentage Uncertainty Reduction by Lookahead Window**				
			5-min	**7-min**	**8-min**	**9-min**	**10-min**
26-Jan-16	1 minute	5 hours	52.21	36.28	31.02	24.79	17.83
31-Jan-16	1 minute	5 hours	47.76	32.73	24.35	14.29	4.69
26-Jan-16	4 seconds	1 hour	30.43	15.11	10.88	0.89	--
31-Jan-16	4 seconds	1 hour	42.25	19.46	8.95	--	--

These initial results were encouraging enough that the study was expanded to include ACE, and results for ACE and frequency deviations are included in Table 3.2, Table 3.3, Table 3.4, and Table 3.5. Some key points to note from this study:

- We are using time-series methods, which means the methods look a certain number of data points into the future. As a result, the results are often better for the 1-minute resolution data than for the 4-second resolution data, though it may seem counterintuitive that lower resolution would be better. The method used starts to taper off in reduction of uncertainty for larger numbers of data points in the look-ahead window. As a result, time-clustering of the data is a key parameter to tune in order to get the most out of the method. We used the original 4-second SCADA data and one-minute clusters averaged from the original 4-second SCADA data, but additional time clustering parameters should be explored. Time-clustering as a strong advantage was an unexpected result from this study.

- The impact of the training period is strong enough to warrant some effort into tuning this parameter as well. Not shown are earlier results that seemed discouraging that used a much longer training period than the results shown. A longer training period gives too much predominance to system states from a different part of the daily operating regime and gives weight to system topologies that are things of the past for the look-ahead windows of interest. Our initial experiments showed a fairly sharp drop-off in results for anything over 5 hours. The results presented are for 1-hour, 3-hour and 5-hour training periods.

- New algorithms came available in the course of performing this study, and we upgraded our methodology to include them. This area of mathematics produces improved algorithms at least yearly, so revisiting the underlying mathematics on a regular basis would ideally be part of the maintenance of any tool based on this type of methodology.

- How much predictability is enough varies according to the intended application of the results and the comfort level of those who will use them. CAISO was looking for at least 60% uncertainty reduction looking ahead 7 minutes, or at least 80% uncertainty reduction looking ahead 3 minutes. New tools based on this kind of approach could assist them in dealing with large and fast system swings.

Table 3.2: Frequency deviations uncertainty reduction summary, 1-minute data resolution

date of data	**Training period**	**Percentage Uncertainty Reduction by Look-ahead Window**								
		1-min	**2-min**	**3-min**	**4-min**	**5-min**	**7-min**	**8-min**	**9-min**	**10-min**
5-Mar-17	1 hour	89.24	81.56	72.78	60.79	48.14	18.17	0.59	--	--
5-Mar-17	3 hours	88.57	77.45	72.73	64.67	54.91	41.51	33.68	25.65	8.77
5-Mar-17	5 hours	89.11	82.06	74.17	64.71	55.40	40.68	31.92	23.61	15.82
6-Mar-17	1 hour	70.92	53.15	37.67	21.55	8.58	--	--	--	--
6-Mar-17	3 hours	72.15	53.77	37.02	20.42	5.73	--	--	--	--
6-Mar-17	5 hours	72.88	55.85	40.69	26.43	13.56	--	--	--	--
26-Jan-16	1 hour	85.90	77.63	69.41	57.16	46.64	18.69	9.12	--	--
26-Jan-16	3 hours	85.74	77.53	69.81	60.22	52.56	35.89	29.85	22.60	16.53
26-Jan-16	5 hours	85.58	77.37	69.74	60.31	52.21	36.28	31.02	24.79	17.83
31-Jan-16	1 hour	91.23	84.15	74.13	60.96	45.47	4.12	--	--	--
31-Jan-16	3 hours	90.20	81.84	75.63	66.80	56.77	34.00	20.91	6.10	--
31-Jan-16	5 hours	86.65	72.77	62.69	54.67	47.76	32.73	24.35	14.29	--

Table 3.3: ACE uncertainty reduction summary, 1-minute data resolution

date of data	Training period	Percentage Uncertainty Reduction by Look-ahead Window								
		1-min	**2-min**	**3-min**	**4-min**	**5-min**	**7-min**	**8-min**	**9-min**	**10-min**
5-Mar-17	1 hour	85.33	74.51	61.00	41.80	20.01	--	--	--	--
5-Mar-17	3 hours	88.06	76.62	64.74	52.14	39.47	13.84	3.00	--	--
5-Mar-17	5 hours	87.74	76.30	64.43	51.42	38.89	17.33	5.66	--	--
6-Mar-17	1 hour	81.41	65.93	47.27	26.82	5.22	--	--	--	--
6-Mar-17	3 hours	80.50	65.16	51.33	39.13	26.63	8.67	--	--	--
6-Mar-17	5 hours	80.82	66.92	53.76	41.13	29.31	9.41	--	--	--
26-Jan-16	1 hour	90.93	81.57	69.14	53.88	36.45	10.74	--	--	--
26-Jan-16	3 hours	90.58	81.72	71.56	59.53	47.05	21.87	10.50	0.24	--
26-Jan-16	5 hours	90.04	81.21	70.54	59.45	48.34	25.32	14.80	4.86	--
31-Jan-16	1 hour	93.02	86.09	75.89	63.22	46.62	5.88	--	--	--
31-Jan-16	3 hours	92.77	86.79	79.57	71.28	61.35	40.48	28.32	14.75	--
31-Jan-16	5 hours	89.85	75.88	69.56	62.86	53.95	32.27	22.03	10.99	1.96

Table 3.4: Frequency deviations uncertainty reduction summary, 4-second data resolution

date of data	Training period	Percentage Uncertainty Reduction by Look-ahead Window								
		1-min	**2-min**	**3-min**	**4-min**	**5-min**	**7-min**	**8-min**	**9-min**	**10-min**
5-Mar-17	1 hour	65.83	56.18	52.68	44.68	33.99	18.05	9.65	2.74	--
5-Mar-17	3 hours	65.22	55.45	52.07	44.15	33.46	17.10	8.98	2.11	--
5-Mar-17	5 hours	64.57	54.74	51.40	43.46	32.76	16.40	8.29	1.48	--
6-Mar-17	1 hour	37.49	16.40	5.95	--	--	--	--	--	--
6-Mar-17	3 hours	40.53	20.13	9.15	--	--	--	--	--	--
6-Mar-17	5 hours	40.13	19.24	8.23	--	--	--	--	--	--
26-Jan-16	1 hour	57.80	50.33	43.06	31.69	30.43	15.11	10.88	0.89	--
26-Jan-16	3 hours	56.76	49.02	41.72	30.76	29.29	14.05	9.81	--	--
26-Jan-16	5 hours	56.16	48.38	41.12	30.18	28.71	13.45	9.21	--	--
31-Jan-16	1 hour	78.24	70.85	62.63	53.21	42.25	19.46	8.95	--	--
31-Jan-16	3 hours	78.52	71.18	62.95	53.48	42.54	19.69	9.17	--	--
31-Jan-16	5 hours	78.34	70.99	62.78	53.31	42.37	19.52	9.01	--	--

Table 3.5: ACE uncertainty reduction summary, 4-second data resolution

date of data	**Training period**	**Percentage Uncertainty Reduction by Look-ahead Window**								
		1-min	**2-min**	**3-min**	**4-min**	**5-min**	**7-min**	**8-min**	**9-min**	**10-min**
5-Mar-17	1 hour	82.17	55.67	20.32	--	--	--	--	--	--
5-Mar-17	3 hours	85.95	73.18	63.35	50.11	35.81	10.62	--	--	--
5-Mar-17	5 hours	86.08	73.38	63.53	50.29	36.01	10.83	--	--	--
6-Mar-17	1 hour	63.10	47.22	33.57	20.12	6.56	--	--	--	--
6-Mar-17	3 hours	63.02	46.07	30.78	16.18	2.36	--	--	--	--
6-Mar-17	5 hours	62.15	46.70	32.44	19.64	6.15	--	--	--	--
26-Jan-16	1 hour	79.00	70.02	59.36	43.92	34.20	13.58	3.78	--	--
26-Jan-16	3 hours	78.68	70.10	60.19	46.27	37.78	13.36	3.50	--	--
26-Jan-16	5 hours	78.21	69.58	59.65	45.71	37.24	12.79	2.90	--	--
31-Jan-16	1 hour	85.27	52.35	--	--	--	--	--	--	--
31-Jan-16	3 hours	90.93	83.19	75.01	65.48	54.45	31.05	19.28	5.78	--
31-Jan-16	5 hours	91.09	83.42	75.21	65.66	54.63	31.23	19.42	5.91	--

3.3 Solar Energy's Role in Regulation Requirements

Regulation as an ancillary service is purchased in the day-ahead market based on day-ahead forecasting of total net load, including day-ahead forecasts of solar and wind generation. The amount of regulation then applied intra-day is based on intra-day forecasting. The magnitude of the difference between the day-ahead forecasts and the applicable intra-day forecast then shows the potential for improving the recommendations for the amount of regulating service to purchase in the day-ahead market.
For the period studied in the cost/benefit analysis, the differences in forecast errors between the day-ahead forecast and the real-time forecast for both solar and wind showed a diurnal pattern as shown in Figure 3.5.

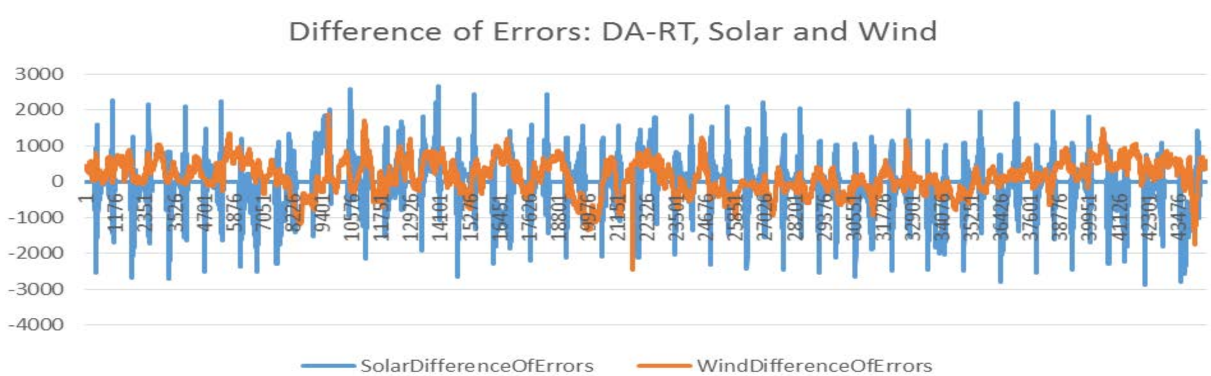

Figure 3-5: Difference in forecast errors between the day-ahead forecast and the real-time forecast for both solar and wind, with the difference in solar forecast errors shown in blue and the difference in wind forecast errors shown in orange.

Solar is often thought to be less predictable than wind, and the day-ahead (DA) forecasts for wind have usually been more accurate than for solar. Inadequate data handling practices for solar may contribute to these outcomes. In any case, large solar swings, on top of the morning and evening ramps, have contributed to poor regulatory scores. However, Figure 3-6 shows that based on regulation requirements during the study period, wind ramps were more significant than solar ramps. This could mean that a misperception of solar power's relative variability, compared to wind, poses another barrier to integration.

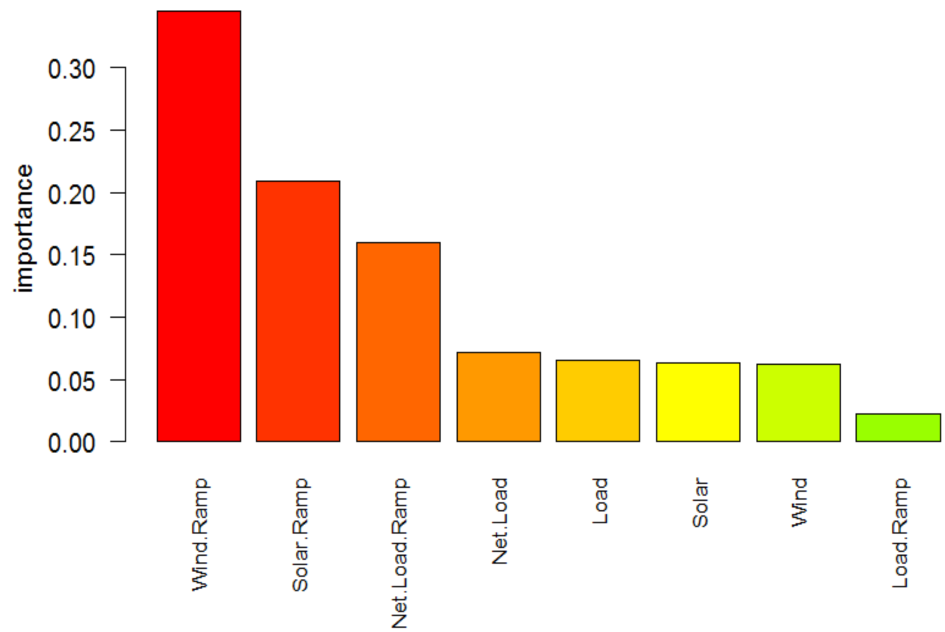

Figure 3-6: Causal factors for Regulation Requirements (RR) during the study period.

4.0 Cost/Benefit Analysis of Operational Tools

PNNL performed a cost/benefit analysis of an operational tool called DARP (Etingov 2018) to implement the uncertainty reduction methods developed in this project (Weimar et. al. March 2018, August 2018). The development cost of the tool was about $200K, compared to overall savings of $2.1M, or 16% of RR costs. Therefore, on month's savings more than paid for the model and tool. The savings came from Regulation Up reserves, not Regulation Down reserves. We also found that 10-minute net-load variability continues throughout the year, and impacts regulation needs significantly. CAISO expects these results to continue throughout the year. The rest of this section describes lessons learned from the cost/benefit analysis.

A fully-accurate cost/benefit analysis of a power systems operational tool or practice would, in many cases, require exhaustive simulations. Historical data can be used to supply certain system conditions, but since the purpose of the new tool or practice would be to produce different operational results and system states than what happened historically, accurate simulations of a regime including that tool or practice require extensive simulation effort.

As a result, sometimes cost/benefit analyses are not run, and decisions are made based on what is believed to be the likely outcome of implementing the new tool or practice. Tools based on new methods, such as probabilistic methods, may face delayed deployments because no one is sure how to estimate the benefits. The example of applying probabilistic methods and tools to power systems operations is particularly apposite – such tools can provide surprising levels of economic benefit in some situations, but the same tool that produced a large benefit in one location may not provide any when applied to a different location. Some type of cost/benefit estimation is needed to at least determine whether the tool would mean a net cost or a net benefit.

Much of the time, whether for probabilistic tools or conventional tools, it is desirable to perform a more approximate cost/benefit analysis, if a methodology can be found that is modest enough in effort to be practical but still accurate enough to be useful. Arriving at such a methodology can be so tricky that it may seem impossible, and it can easily seem that the only way to be sure of the result is to go for the monumental simulations approach. This does not have to be the case, if a certain amount of examining and re-examining of assumptions is carried out by the right team.

A webinar detailing the example approximate cost/benefit analysis in this report and an overview of the recommended best practices can be found at:

4.1 Selecting the cost/benefit analysis project team

The team needed to produce a useful result with limited budget and effort has two key elements:

- Power systems operations engineers from the system and area of control in question and who understand the tool/methodology being analyzed
- Economists with expertise in cost/benefit analyses

Further, a separate review team should be determined, including someone who can review the analysis and report from the perspective of the viewpoint of any governing body or utilities commission that may need to verify the work or weigh in on the decision, as shown in Figure 4-1. While an extensive team may seem safer in order to make sure enough viewpoints are included, too large a team will make the cost/benefit effort more expensive. To achieve a useful result with a limited budget, it is recommended to keep the team small and carefully-chosen. It is particularly important not to let the size of the analysis team grow large enough that the budget for review is impacted.

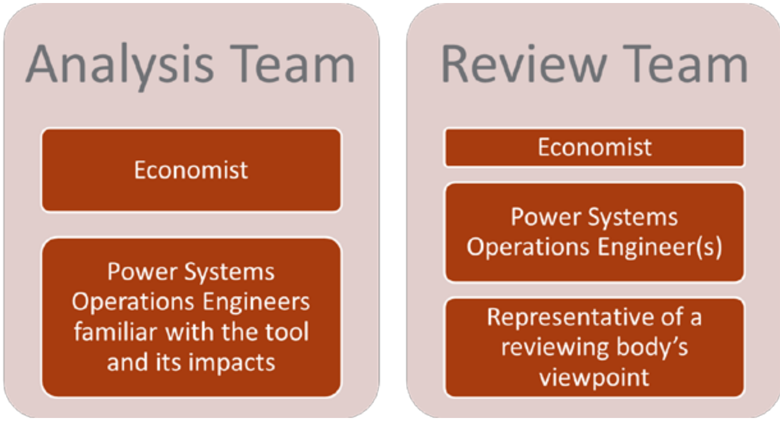

Figure 4-1: The key minimum personnel in the project team; other personnel may be desired.

The right team would include power systems operational engineers who have a deep understanding of the area of control to be impacted and at least some of whom have a clear idea of how the proposed new tool will provide benefit to the operation of the system. It can be helpful if the team includes power engineers who have doubts about how strongly the tool will benefit the operation of the system.

The team needs at least two economist experts in cost/benefit analyses – one leading the economic analysis and one providing critical review. It is highly recommended to use economists or other personnel with a strong finance background for this work, and the economist leading the analysis should ideally be the head of the project. Engineers with experience in cost/benefit analysis can suffice, but the fundamental differences in perspective and the increased methodological expertise of a trained economist will, in most cases, yield better results more clearly applicable to the economic and other concerns of the business making the decision. Building some time into the project for the economist and the engineers to iterate to a strong understanding of what each brings to the project may be necessary, unless the task can be given to a team that already has a strong history of such pairing.

4.2 First steps

The project's beginning will involve a series of discussions in which the power engineers help the economists understand what they believe to be the benefits, costs, and other downsides to the proposed tool or methodology. This may sound easy, but often the approach to getting the engineer to provide this information is to get the engineer to discuss what the tool does, how it does what it does and why the tool is important. In these discussions, the engineers will provide the information required to glean what is a benefit. This generally takes a few discussions for clarity and to bring out details.

As the team carries on these discussions, the team can also review the literature to determine if any of the tool/methodology's attributes have been previously valued, or if similar tools/methodologies have been reviewed. This will save time and effort in the long run and may identify other benefits and costs, which can then be discussed with the project team.

At the same time or prior to this, a clear scope of effort needs to be determined, in terms of how much budget and effort is available for the cost/benefit analysis and what level of approximation is desired, bearing in mind that the lower the budget, the more approximate the result will be. For many probabilistic tools and methodologies, determining whether the tool/methodology will be a net cost or net benefit and providing an order of magnitude of that net cost or net benefit is a desirable first outcome and sufficient to determine whether to pursue integration of the tool/methodology into operations. The scope should also include authorizing the team to clearly state factors left out of the analysis and why, which may be for reasons of scope, infeasibility due to the data available, or because certain factors are determined to have no bearing on the final business decision of whether the tool/methodology will be used by that organization or when it will be deployed.

Example: A new probabilistic tool may be of primary interest because it will help the organization avoid regulatory penalties, but the decision on when to implement the tool or how to make a case to an advisory board or utilities commission may be based on whether it provides economic benefit aside from the impact on probability of regulatory penalties. To save time and budget, determining and carrying out a methodology to estimate savings in penalties might be left out, since it is not impacting the decision the organization currently needs to make.

As a list of agreed-upon benefits and costs develops, for each identified possible cost and benefit, note possible methods by which each cost or benefit might be estimated and what data might be needed. At this stage, rule out estimation methods that are well beyond the scope and budget available, and brainstorm for approximations or proxy estimates for the desired information. Having a varied team including both power engineers and at least one expert economist helps a great deal in coming up with alternate methodologies, and literature searches may help with this as well.

4.3 Data needs and availability

Data availability often plays a larger role in determining methodology for this kind of study than engineers tend to expect; data may turn out to be unavailable or require more effort to obtain than the scope and budget of the cost/benefit analysis will allow. Key factors include who owns the data and how accessible it is (including what processing and cleanup it might need), weighed in light of who will later read the analysis and need to be able to review or replicate the process.

A common mistake is to assume data is available that turns out to be unavailable or to assume data is much more easily acquired than it is when it comes time to gather it. As a result, it becomes important to get samples of key data as early on in the process as possible, because the effort required to acquire the data can’t be fully known until this is done.

5.0 Conclusions and Recommendations

When there are wide intermittent swings in a system's control performance due to intermittent resources in the system, time-series uncertainty reduction methods can be used to gain enough predictability to use in operational control strategies and tools.

- Further research is needed on the methods tested in this project to determine the best parameters for the methods used – with further testing, even better results are likely than what was found.

- It is recommended that other types of uncertainty reduction based on other machine learning and deep learning techniques be investigated for the same purposes.

The type of variable generation resource that contributes most to a particular system phenomenon or problem should not be assumed but should be tested. Our investigation showed that wind variability in the CAISO system drove the need for regulation resources for the period studied more than solar variability, despite the higher penetration of solar. Similar analysis for other time periods is recommended.

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Appendix A ACE Plots

This appendix contains additional data on ACE variability reduction, in support of Section 3.1. On each page of plots, weekdays appear at the top and weekends appear at the bottom. In all periods of the year and all hours of the day, pooling resulted in less ACE variability.

- Balancing Area 1
    - January-February 2015, Figure A-1and Figure A-2
    - March-May 2015, Figure A-3 and Figure A-4
    - June-August 2015, Figure A-5 and Figure A-6
    - September-November 2015, Figure A-7 and Figure A-8
    - December 2015-February 2016, Figure A-9 and Figure A-10
    - March-May 2016, Figure A-11 and Figure A-12
    - June-August 2016, Figure A-13 and Figure A-14
    - September-November 2016, Figure A-15 and Figure A-16
    - December 2016, Figure A-17 and Figure A-18
- Combined Balancing Areas 1-3
    - January-February 2015, Figure A-19 and Figure A-20
    - March-May 2015, Figure A-21 and Figure A-22
    - June-August 2015, Figure A-23 and Figure A-24
    - September-November 2015, Figure A-25 and Figure A-26
    - December 2015-February 2016, Figure A-27 and Figure A-28
    - March-May 2016, Figure A-29 and Figure A-30
    - June-August 2016, Figure A-31 and Figure A-32
    - September-November 2016, Figure A-33 and Figure A-34
    - December 2016, Figure A-35 and Figure A-36

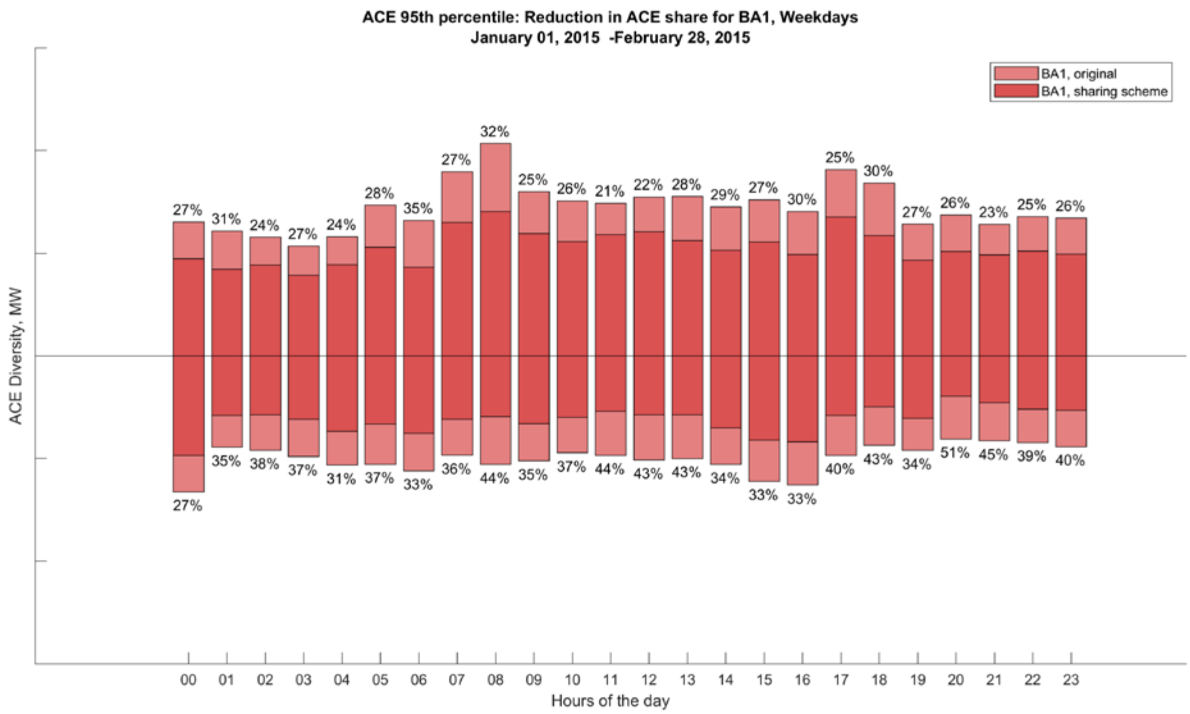

Figure A-1: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in January-February 2015

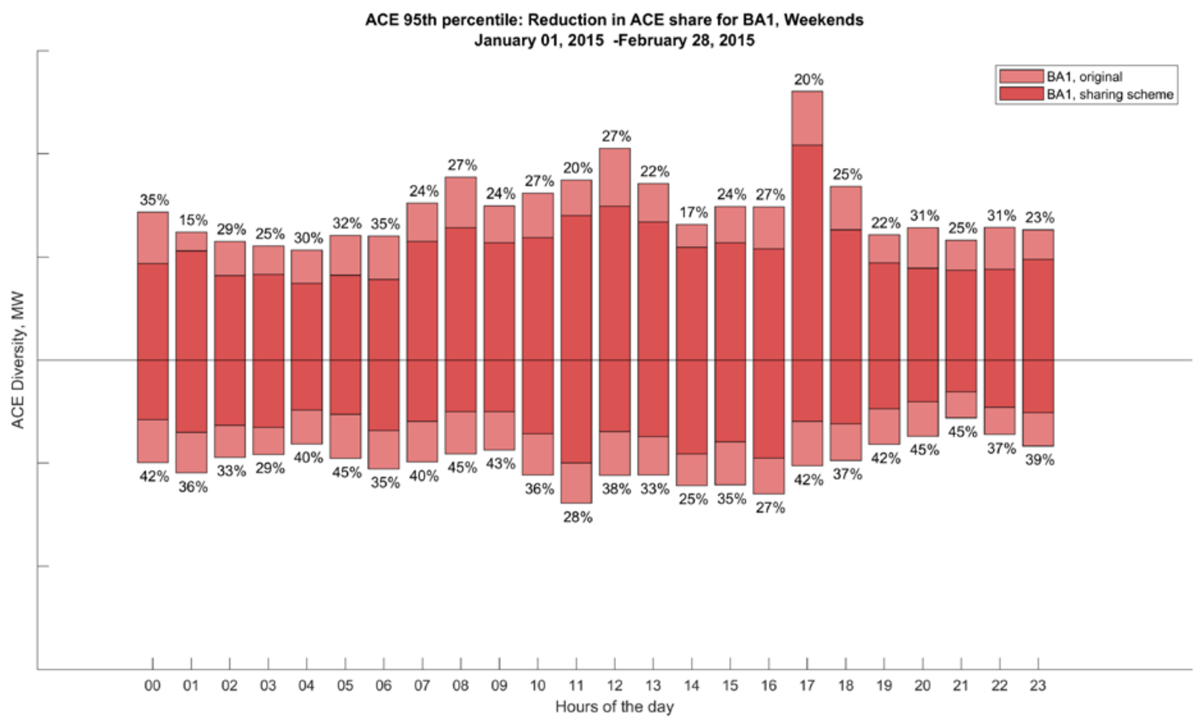

Figure A-2: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekends in January-February 2015.

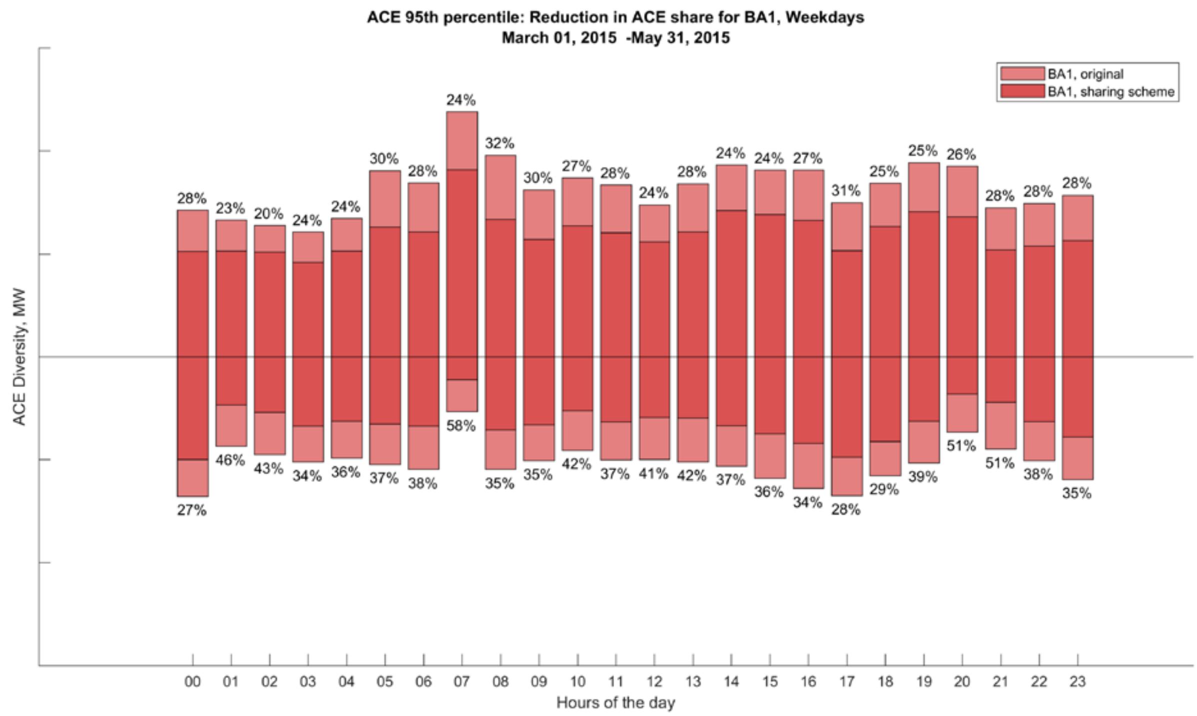

Figure A-3: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in March-May 2015.

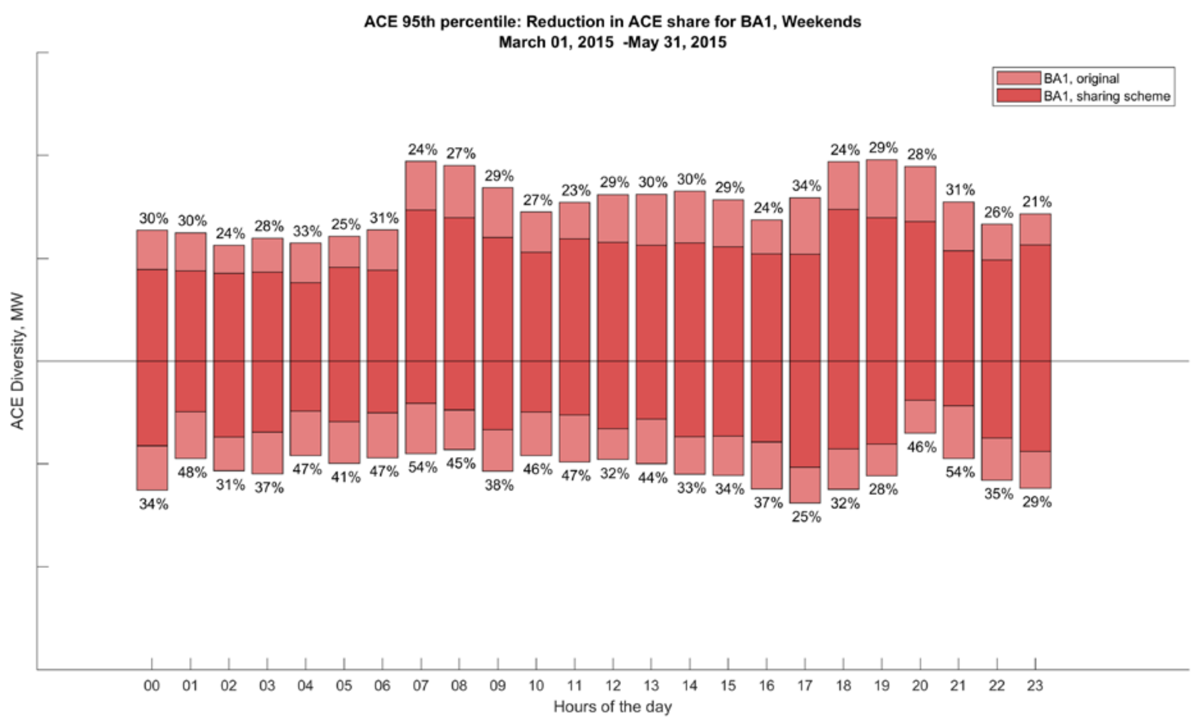

Figure A-4: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekends in March-May 2015.

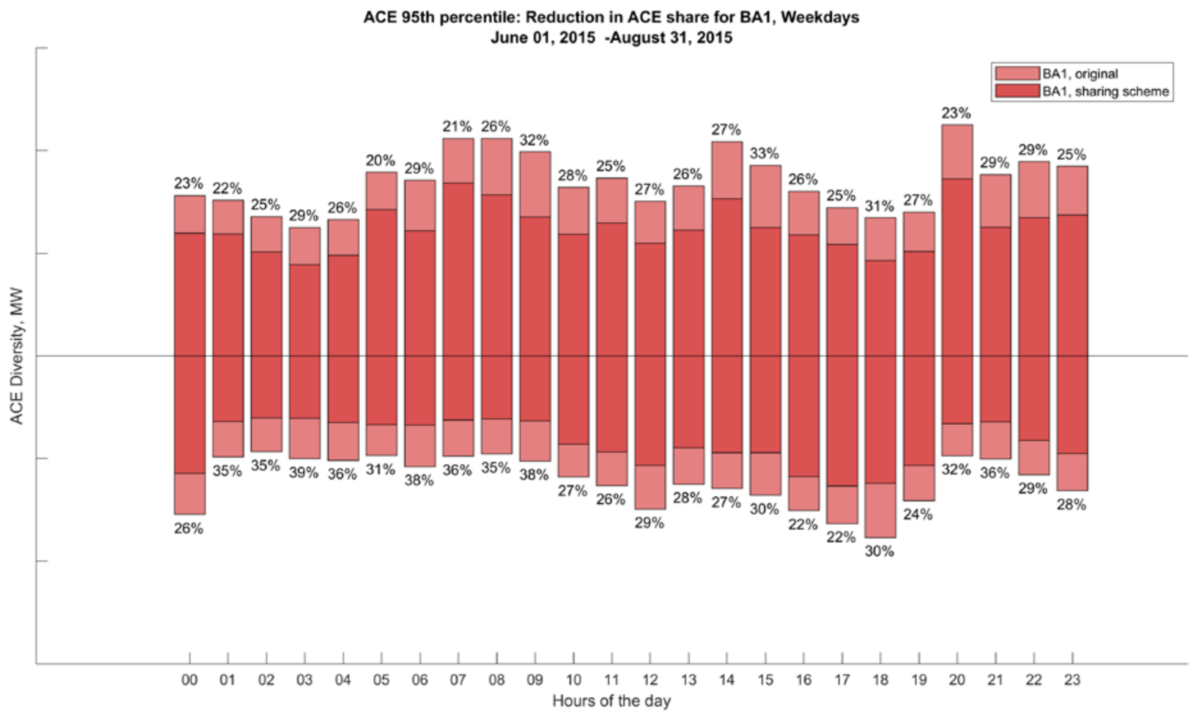

Figure A-5: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in June-August 2015.

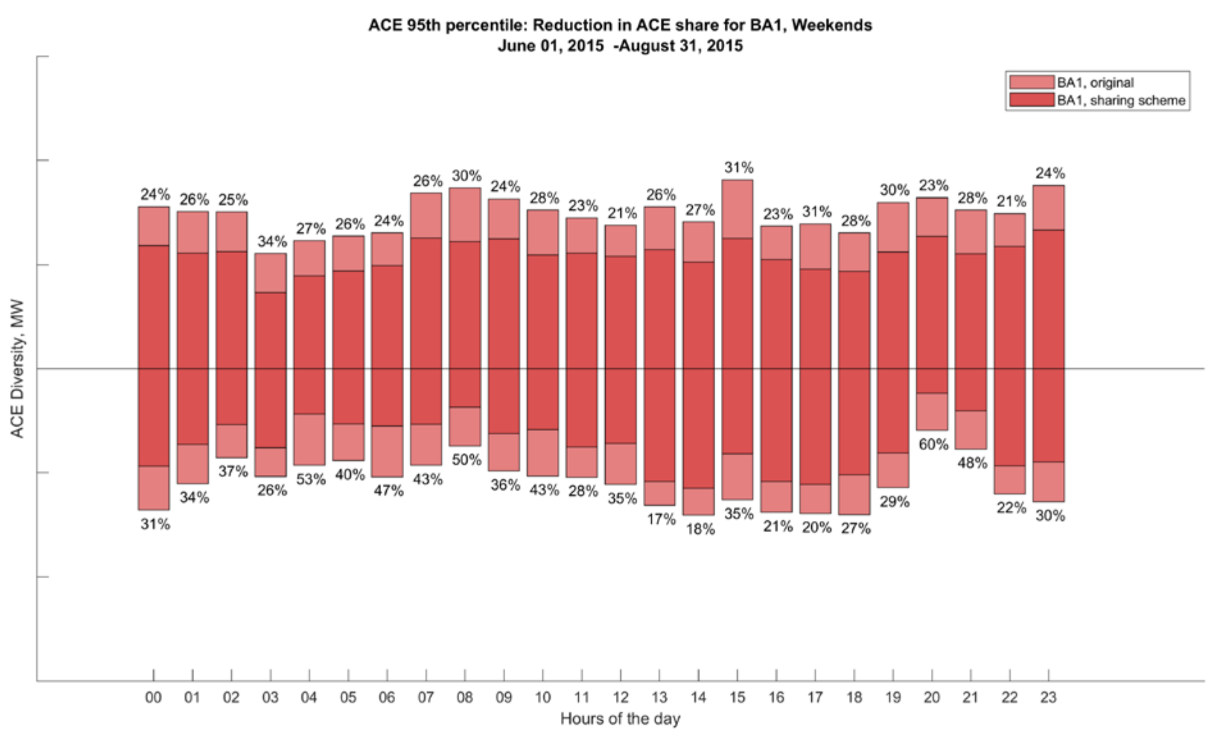

Figure A-6: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekends in June-August 2015.

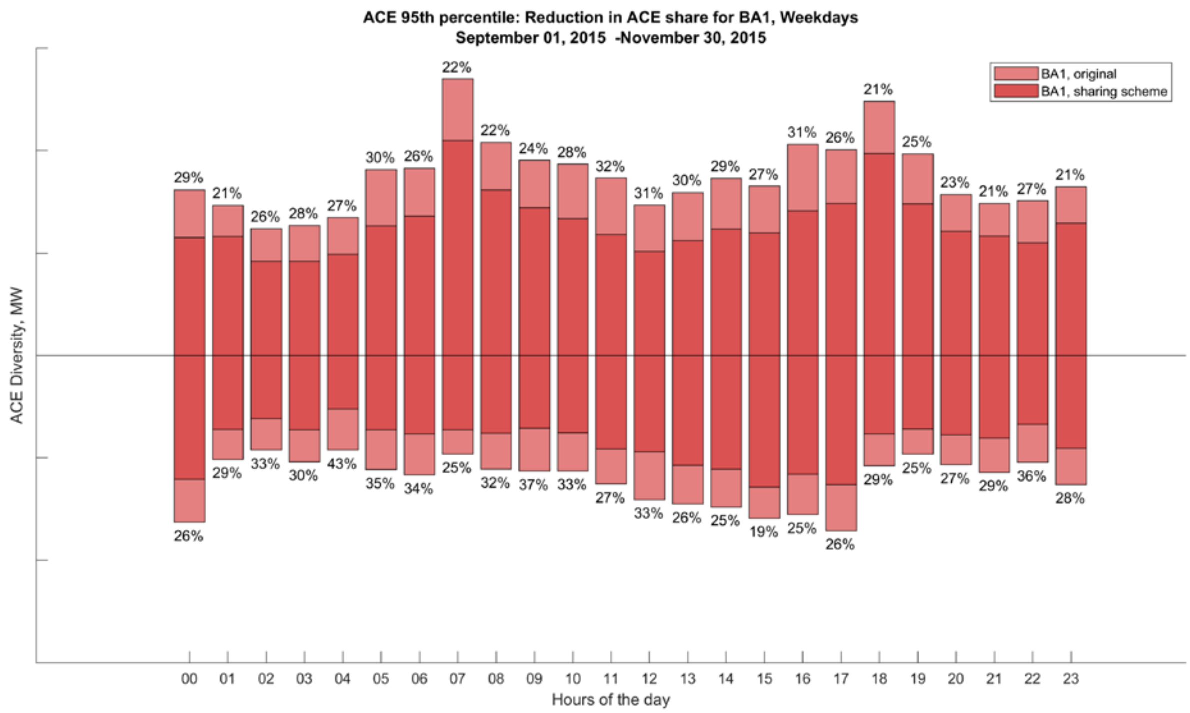

Figure A-7: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in September-November 2015.

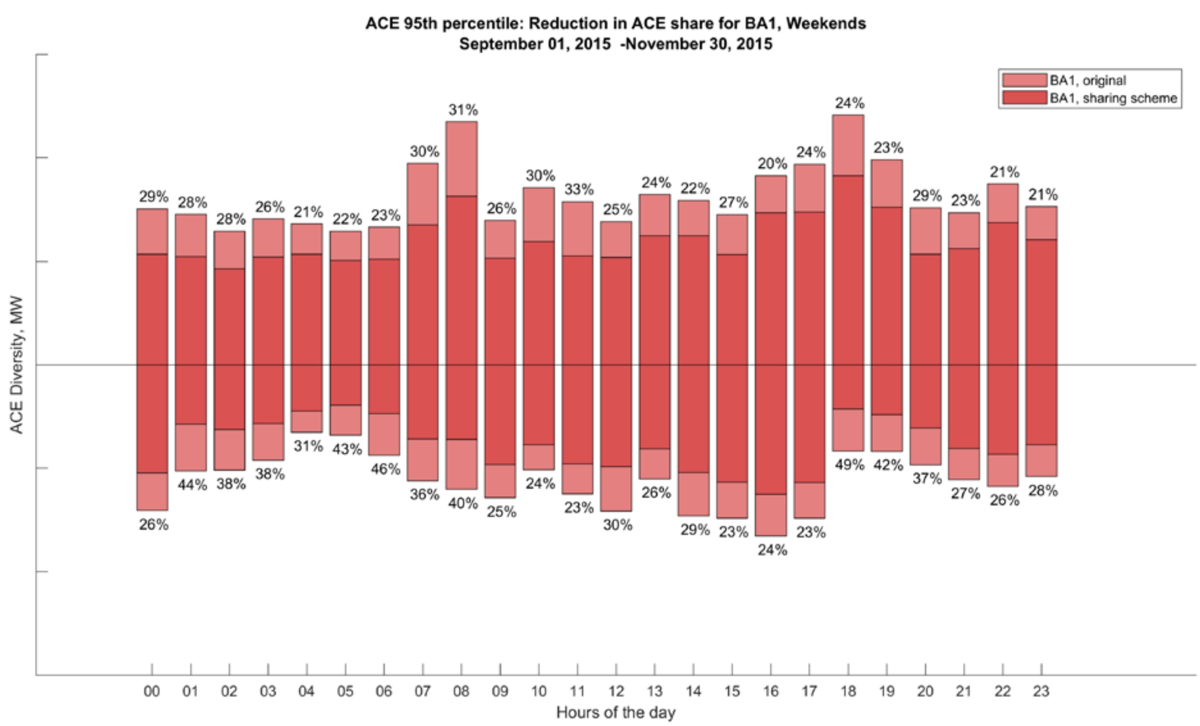

Figure A-8: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in September-November 2015.

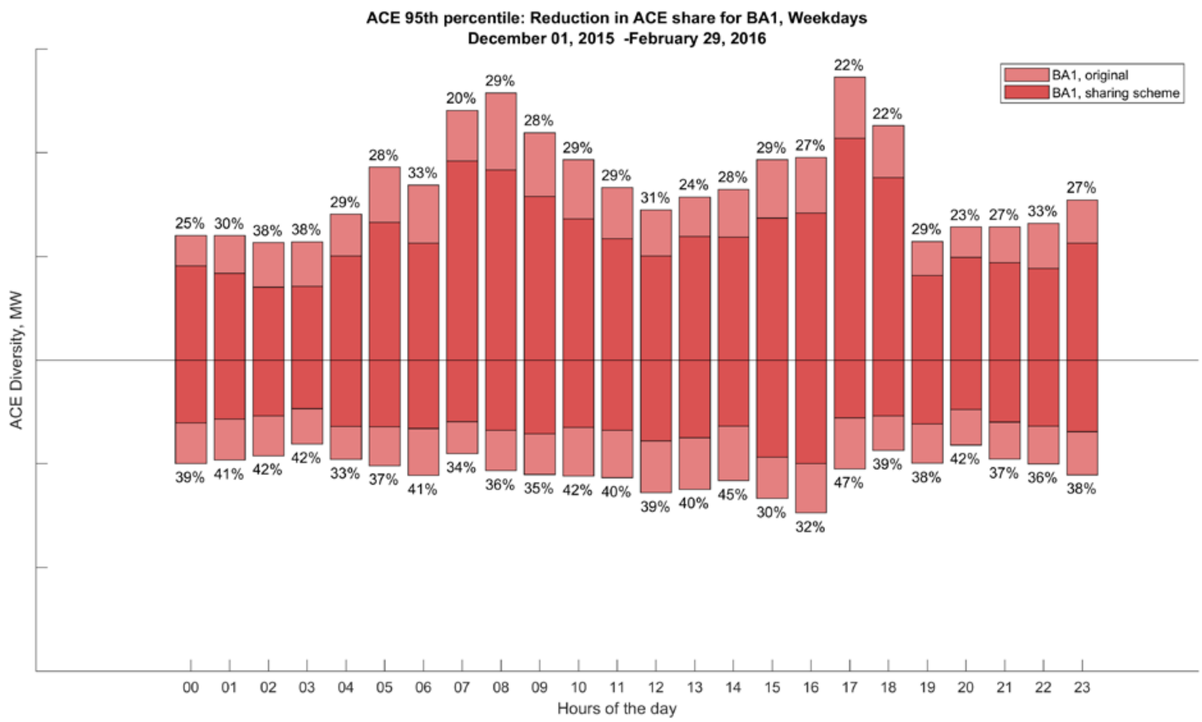

Figure A-9: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in December 2015 - February 2016.

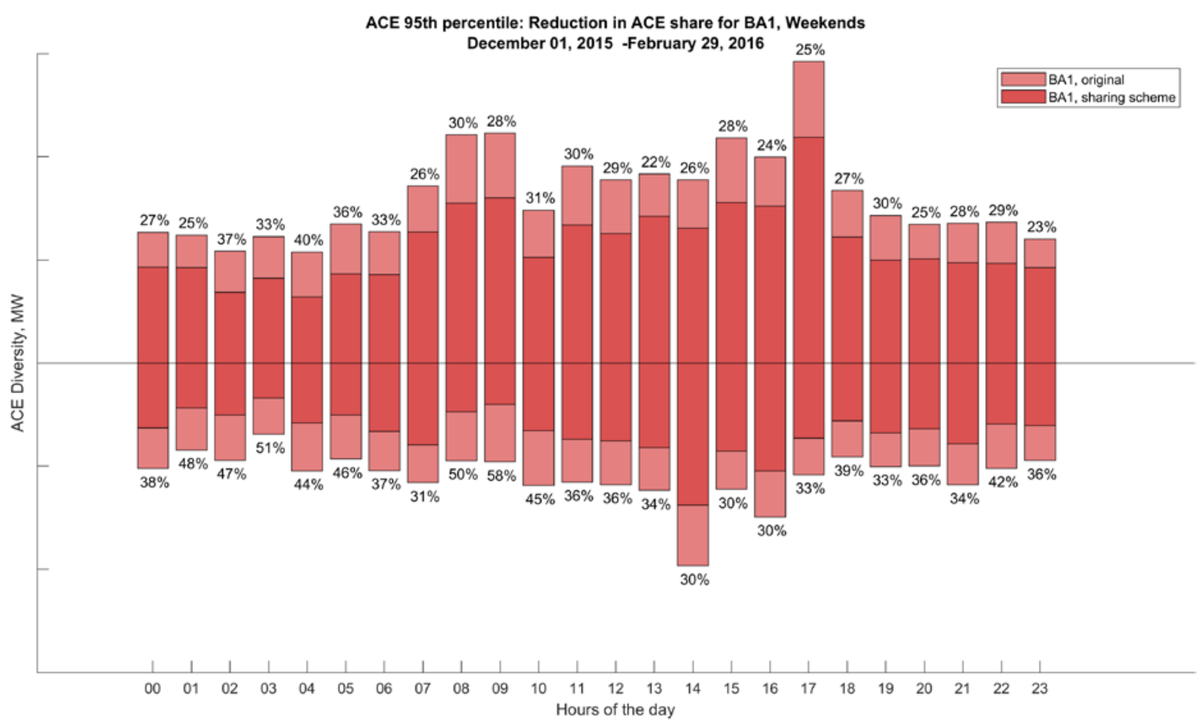

Figure A-10: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekends in December 2015 - February 2016.

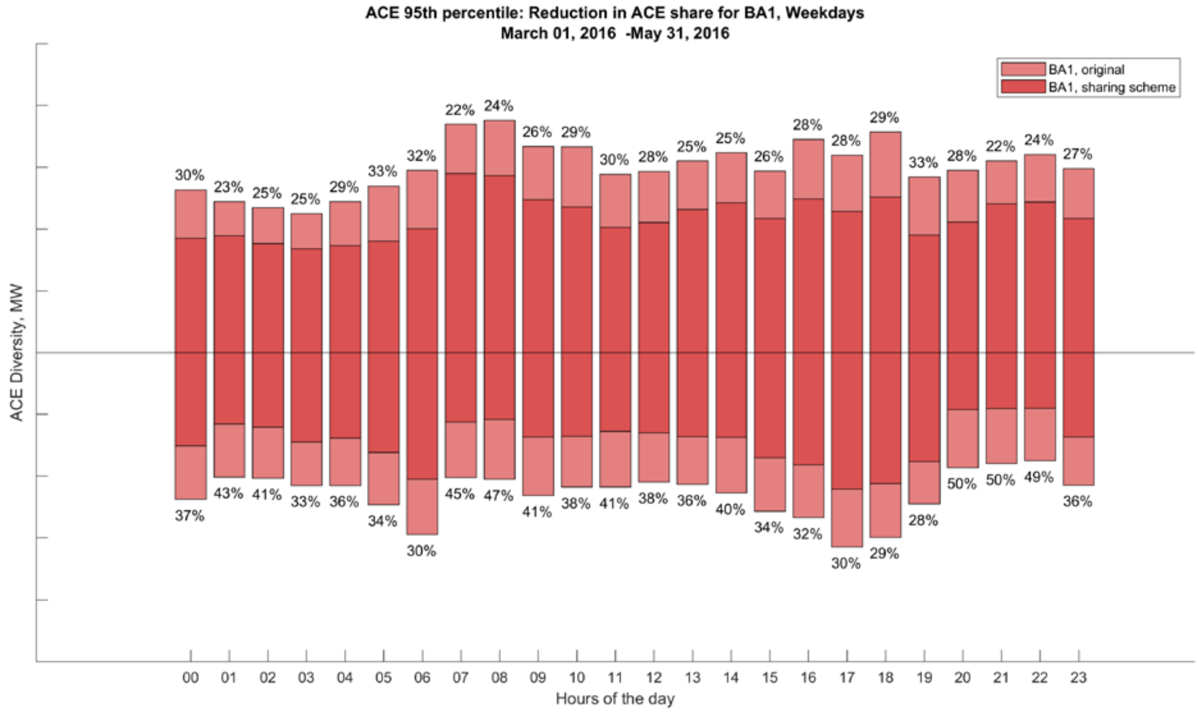

Figure A-11: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in March - May 2016.

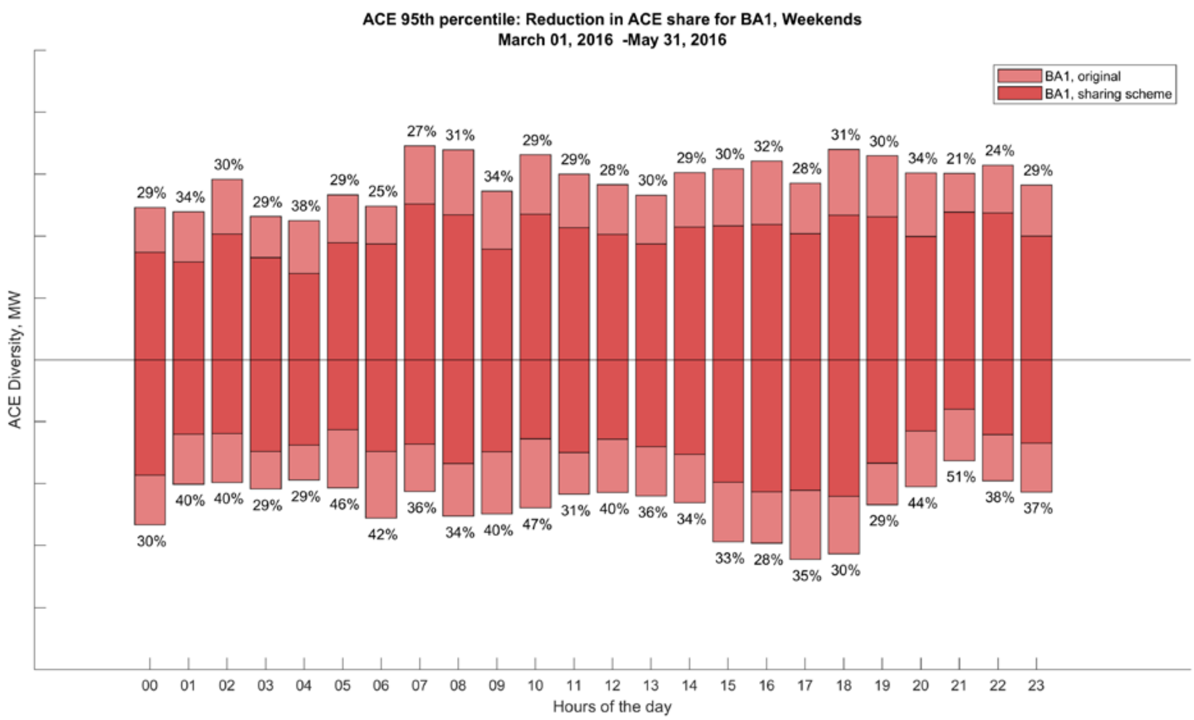

Figure A-12: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekends in March - May 2016.

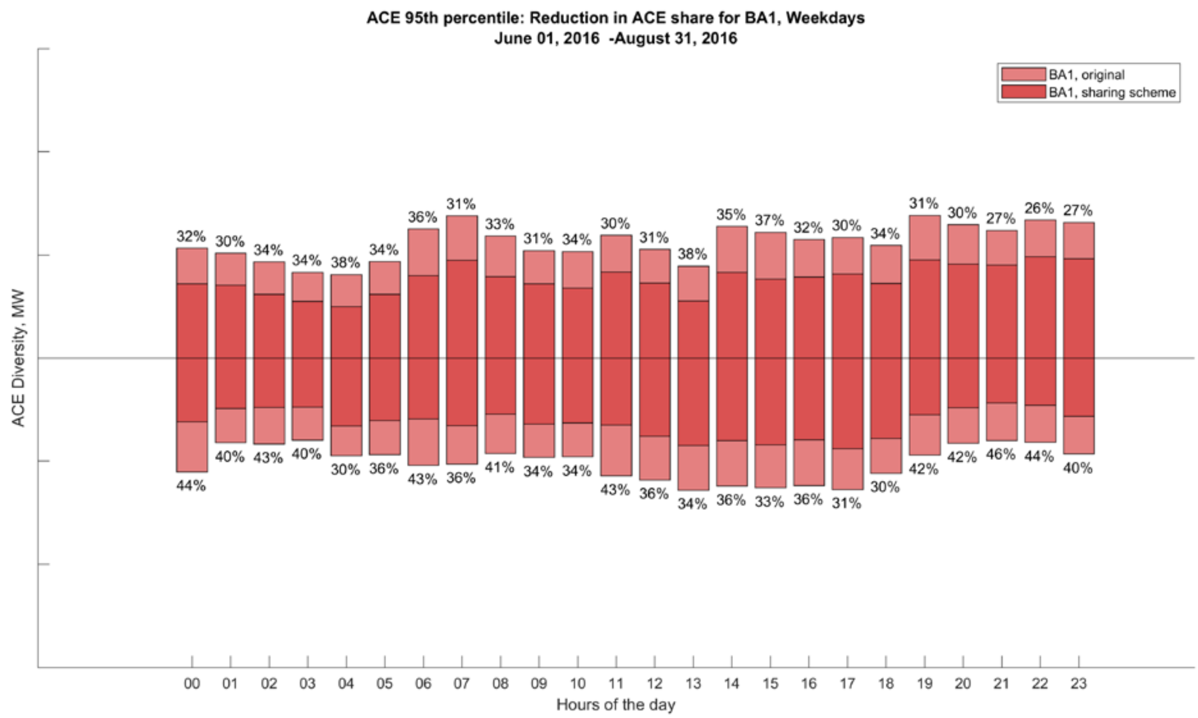

Figure A-13: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in June - August 2016.

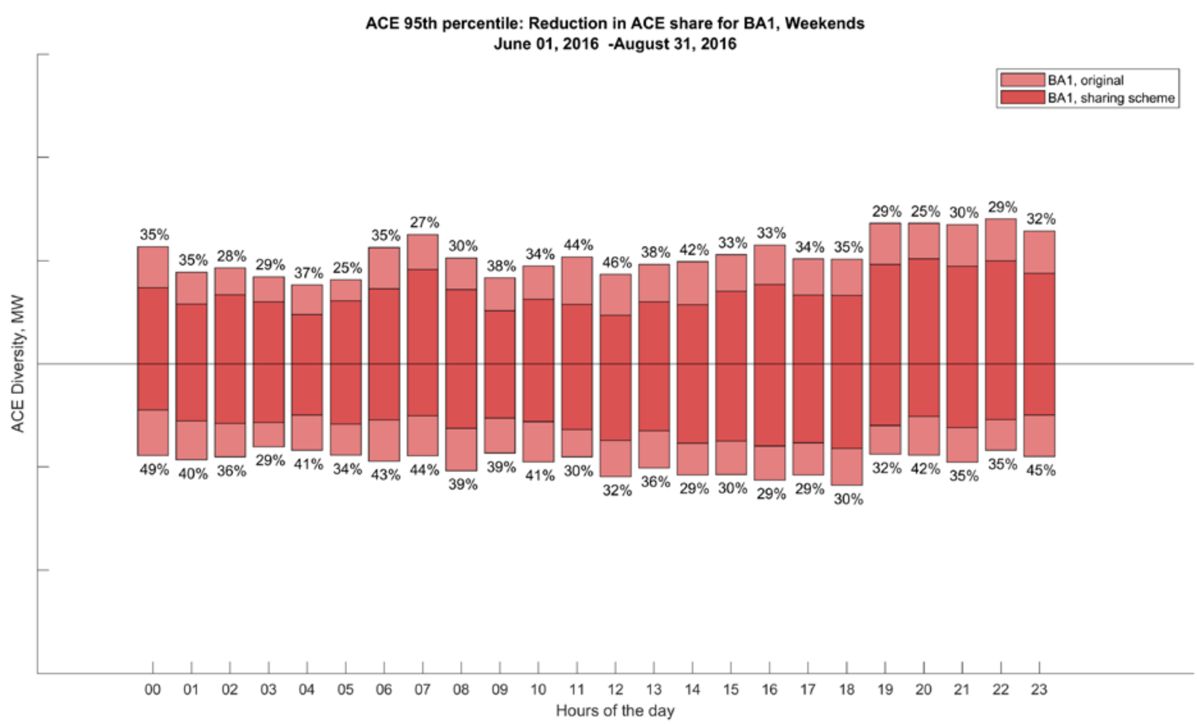

Figure A-14: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekends in June - August 2016.

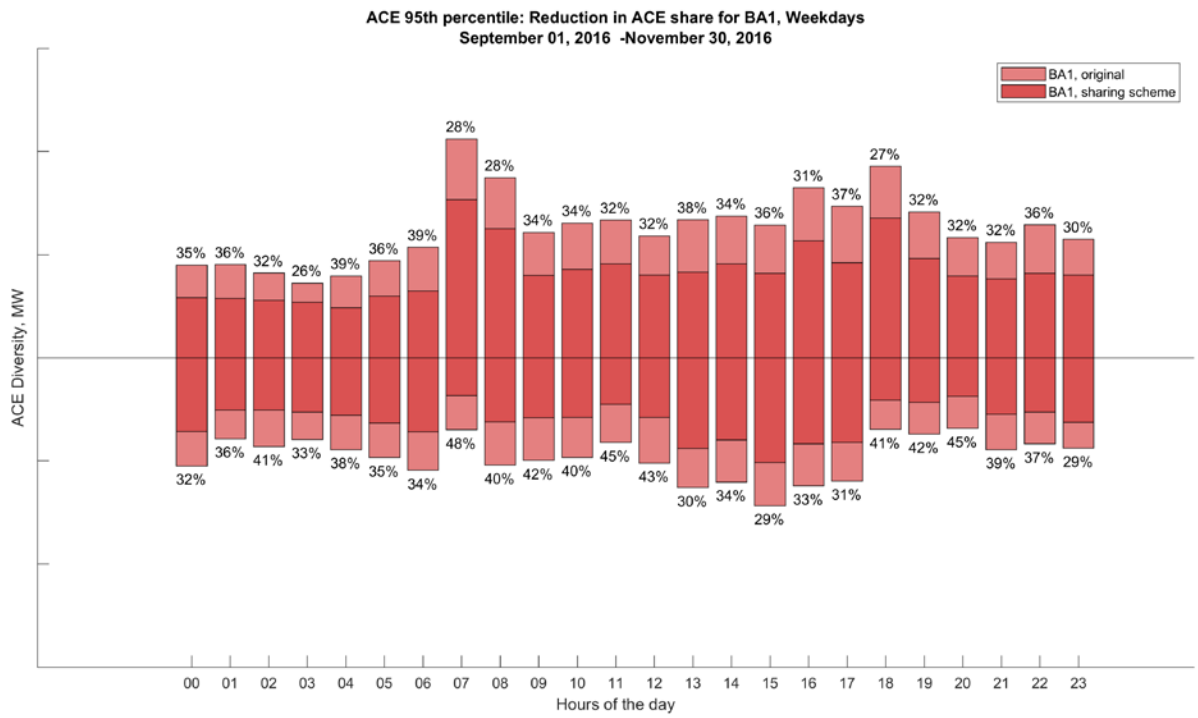

Figure A-15: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in September-November 2016.

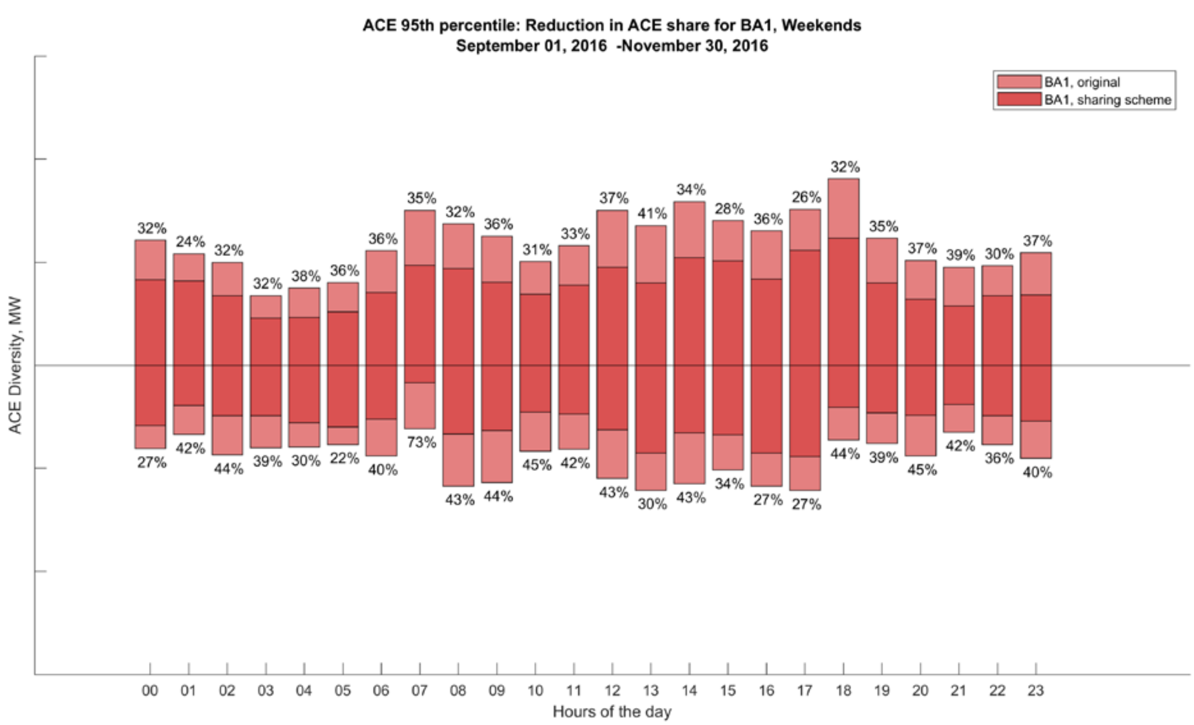

Figure A-16: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekends in September-November 2016.

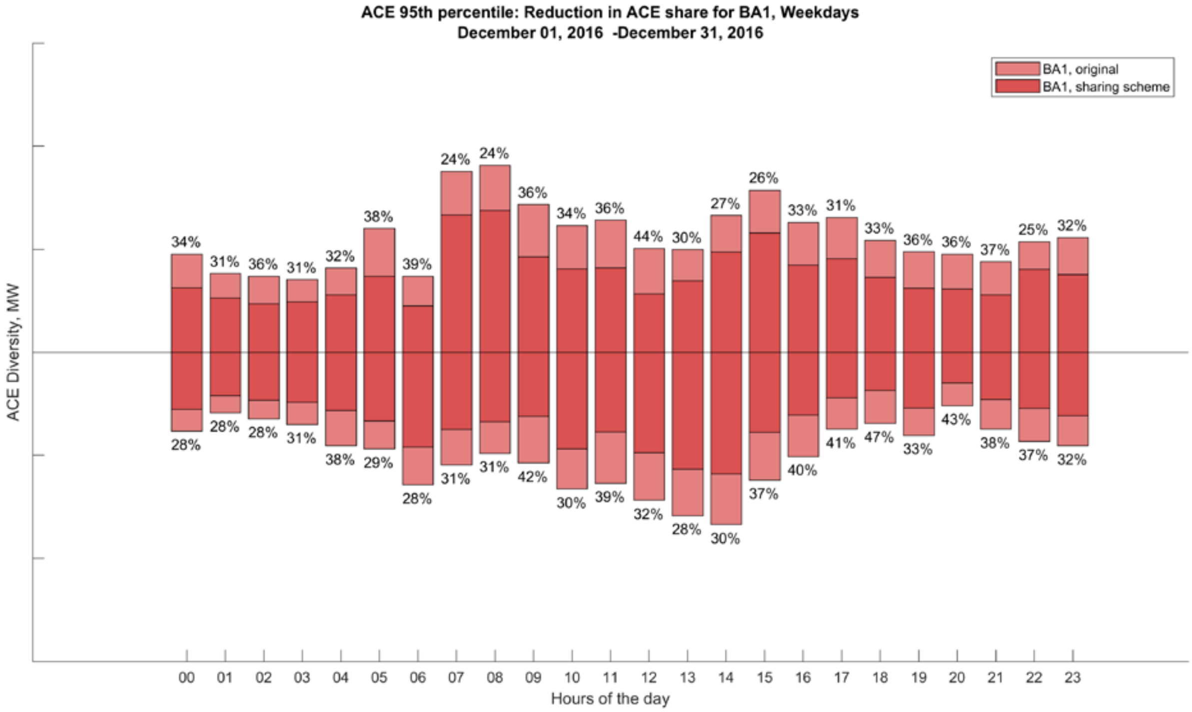

Figure A-17: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekdays in December 2016

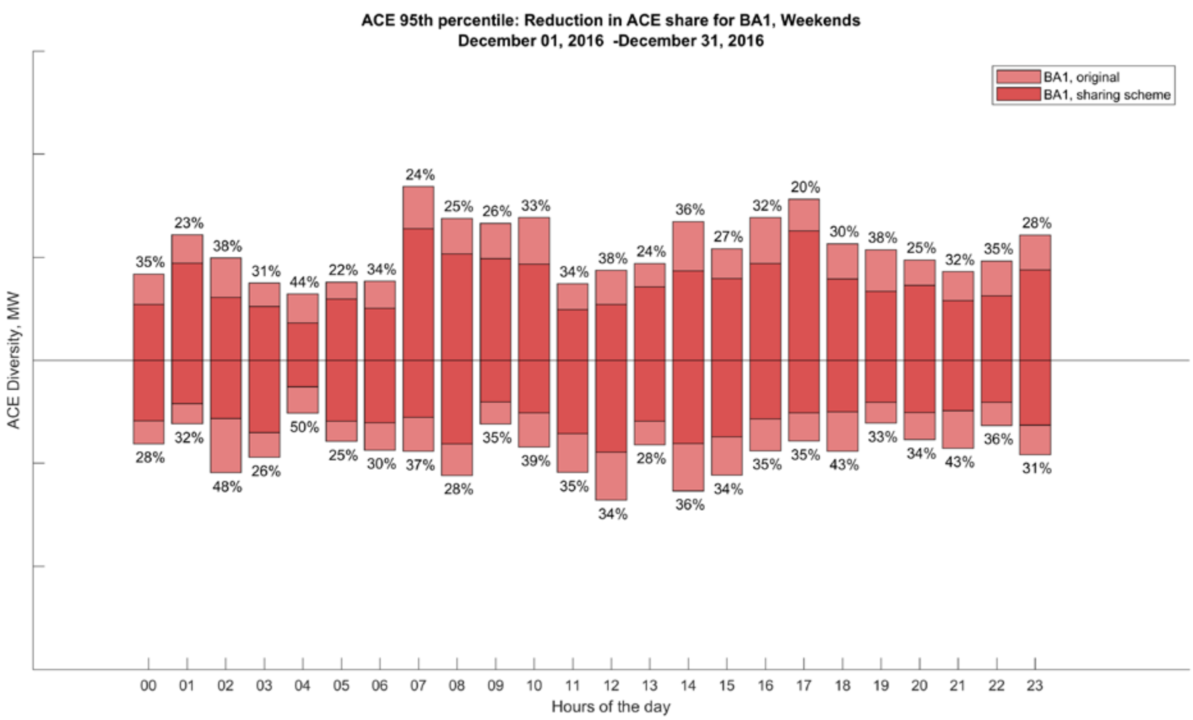

Figure A-18: Reduction in share of ACE variability (95th percentile) responsibility for BA1, for weekends in December 2016.

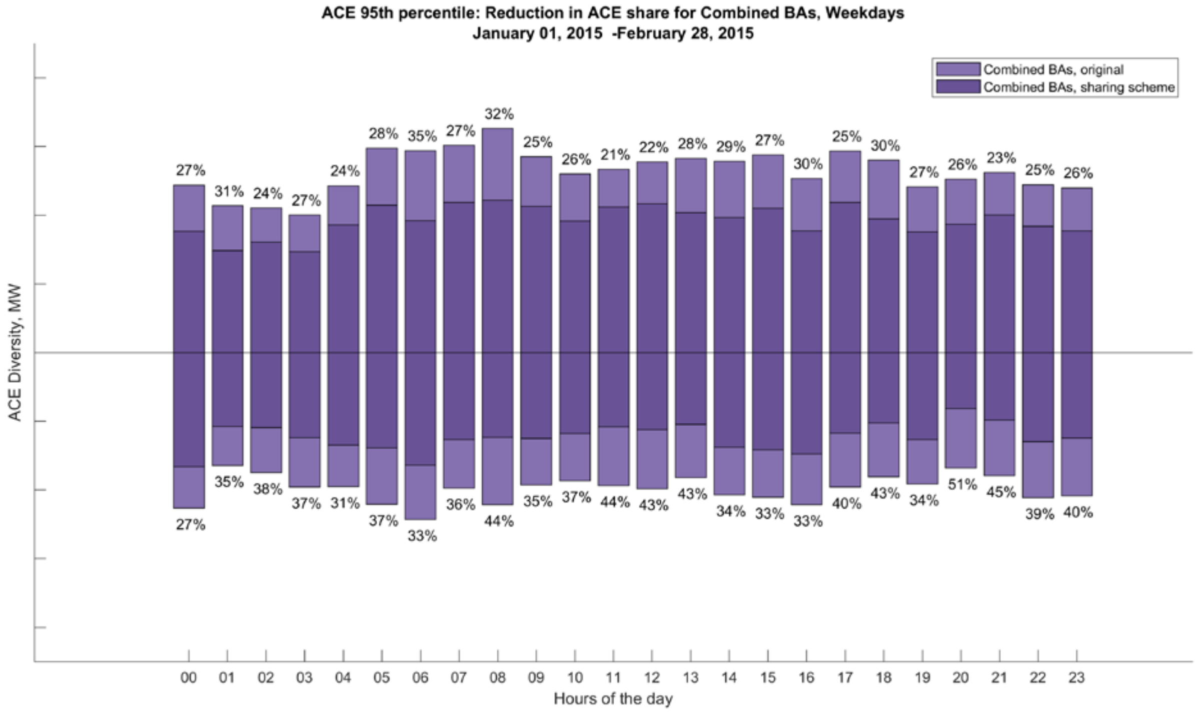

Figure A-19: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in January - February 2015.

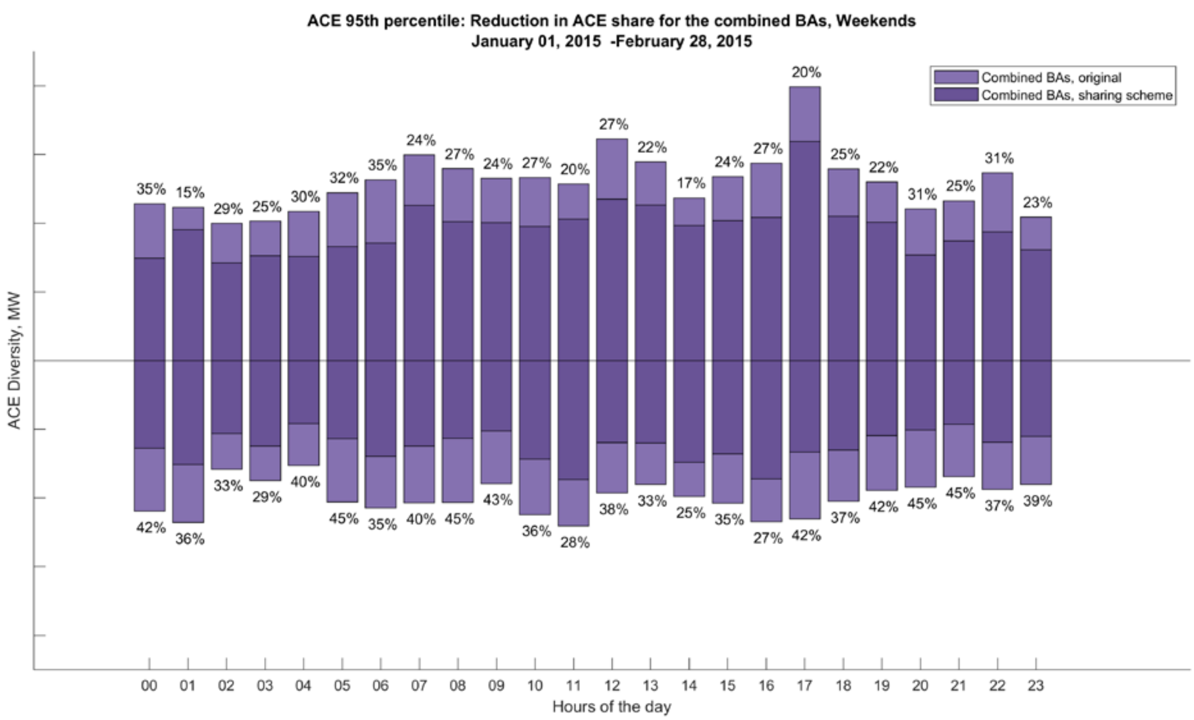

Figure A-20: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekends in January - February 2015.

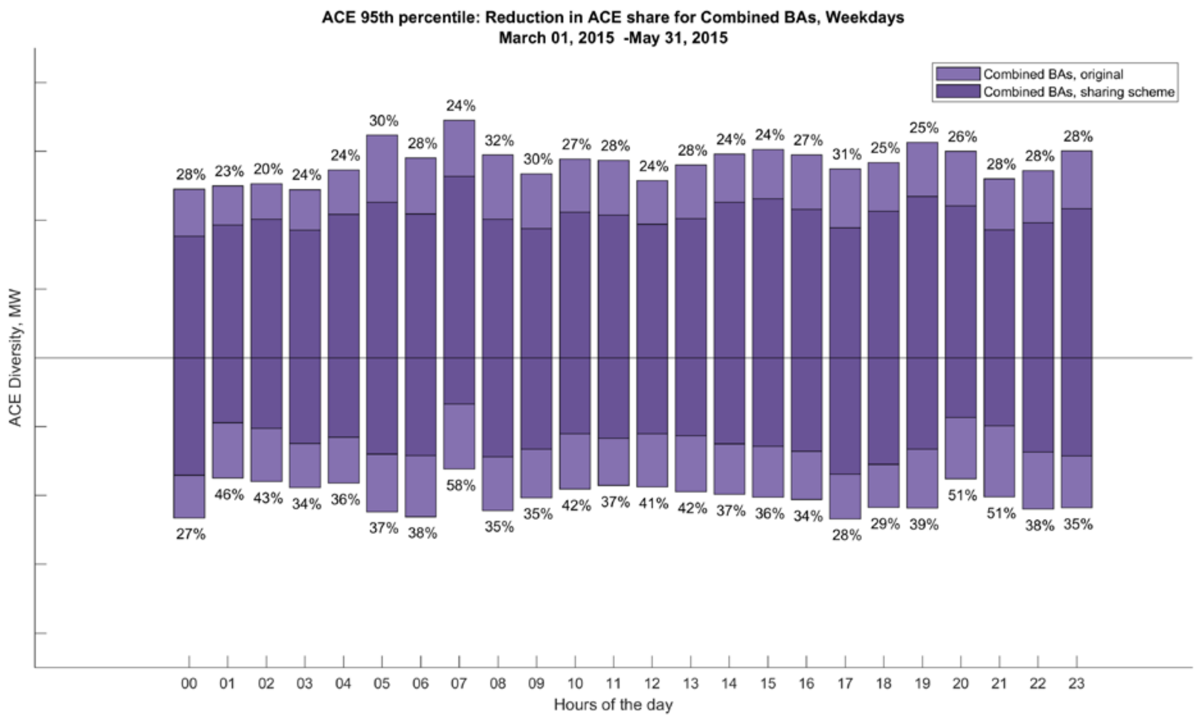

Figure A-21: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in March - May 2015.

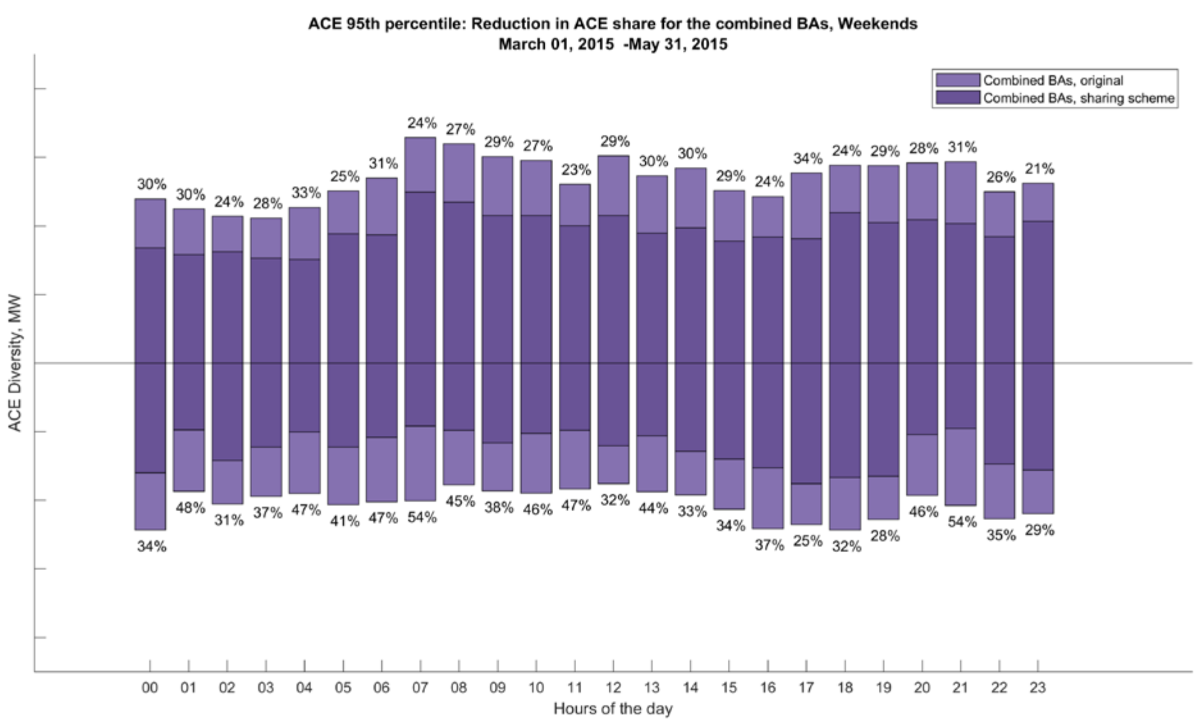

Figure A-22: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekends in March - May 2015.

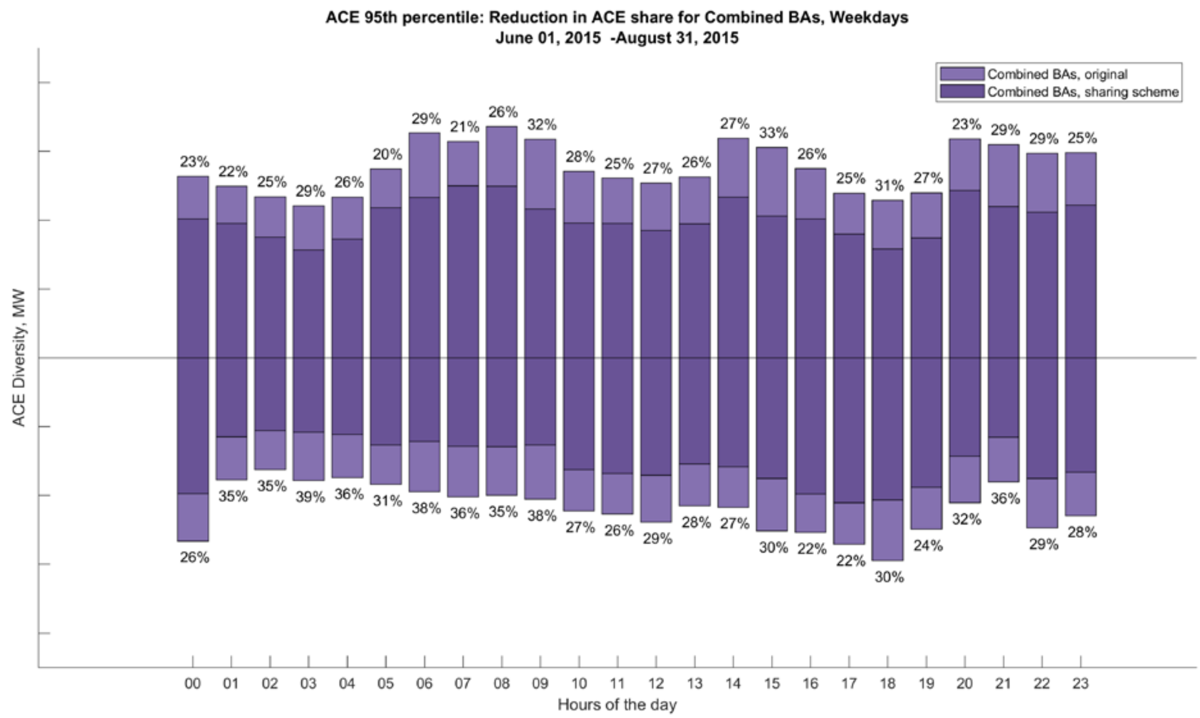

Figure A-23: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in June -August 2015.

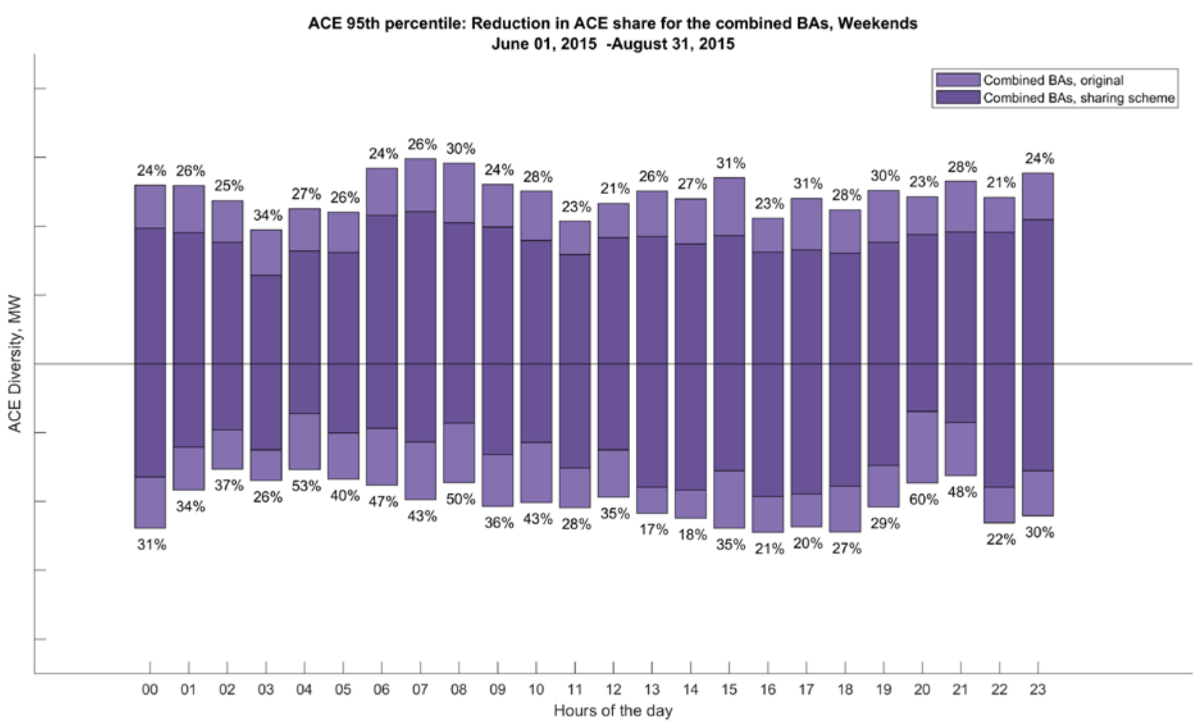

Figure A-24: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekends in June -August 2015.

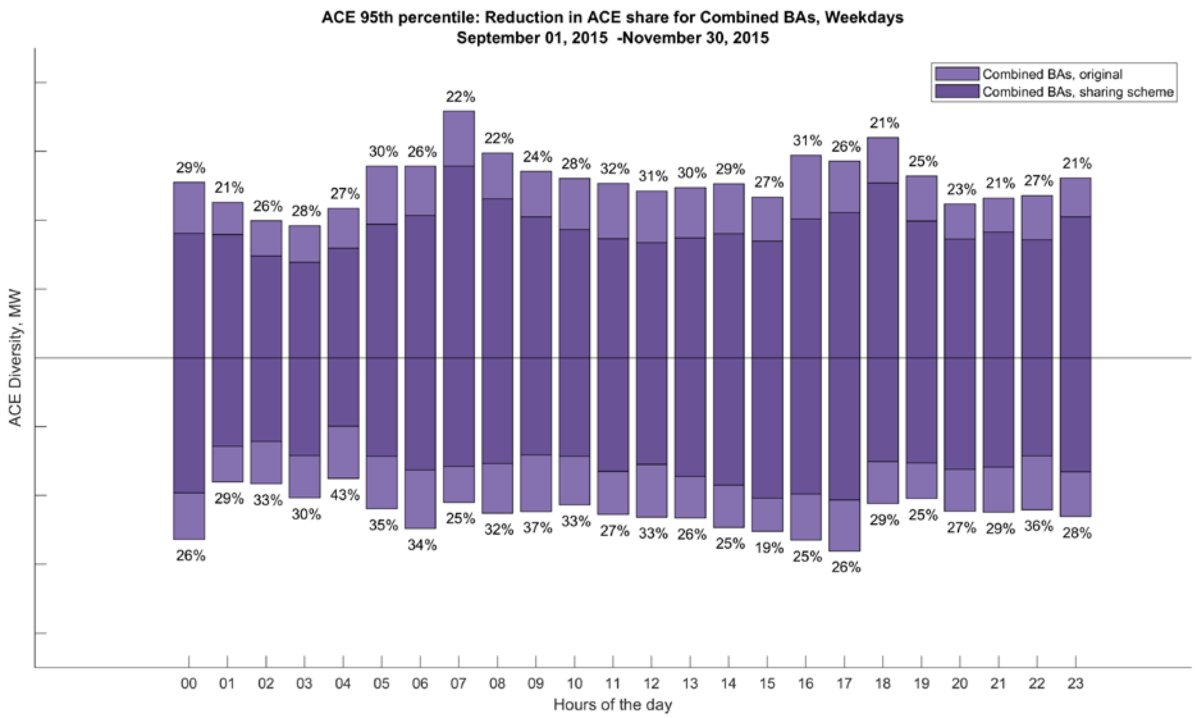

Figure A-25: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in September-November 2015.

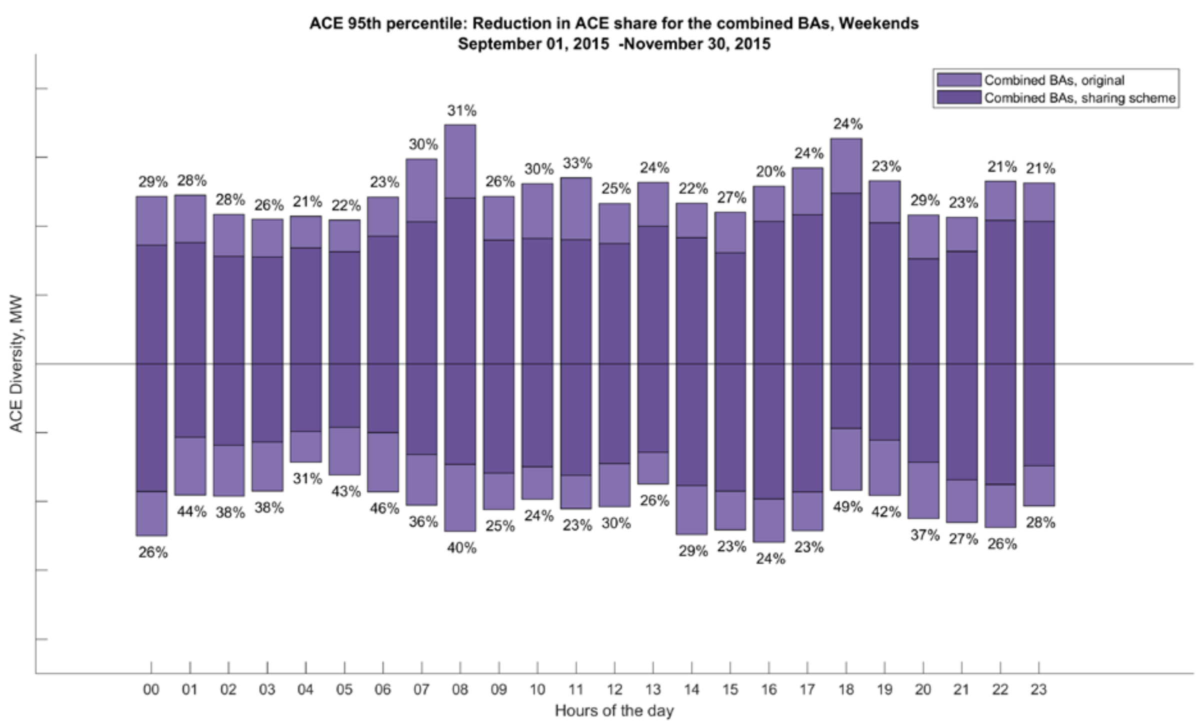

Figure A-26: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekends in September-November 2015.

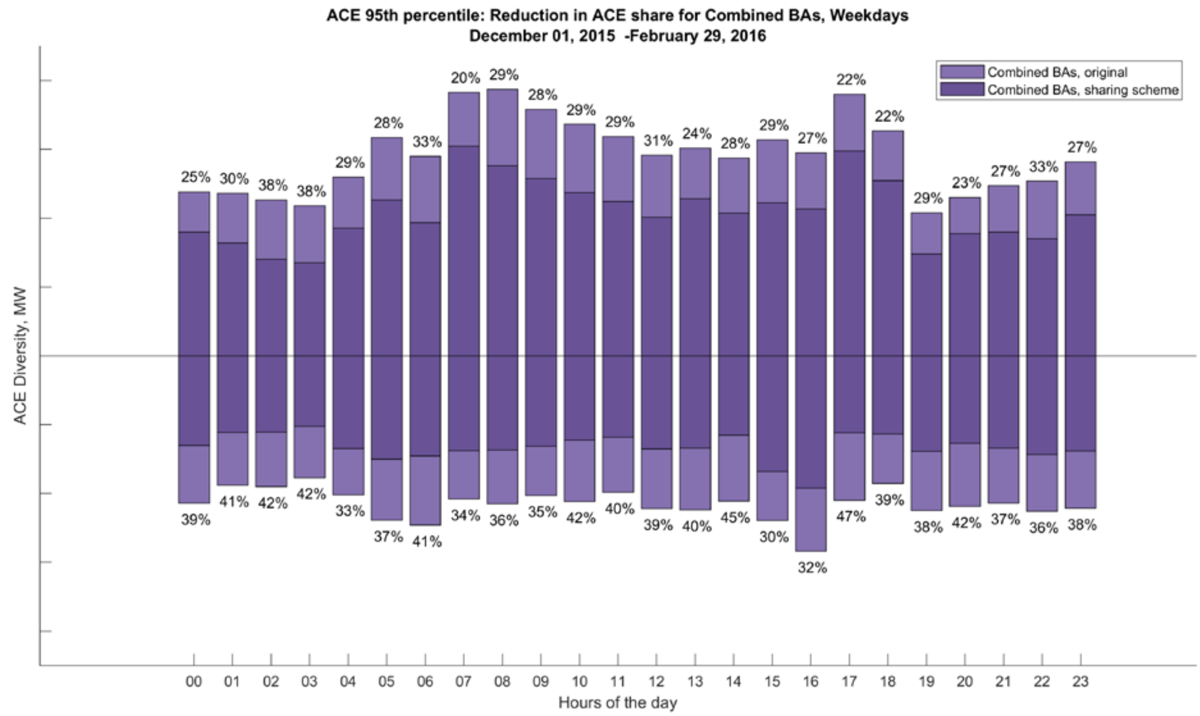

Figure A-27: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in December 2015-February 2016.

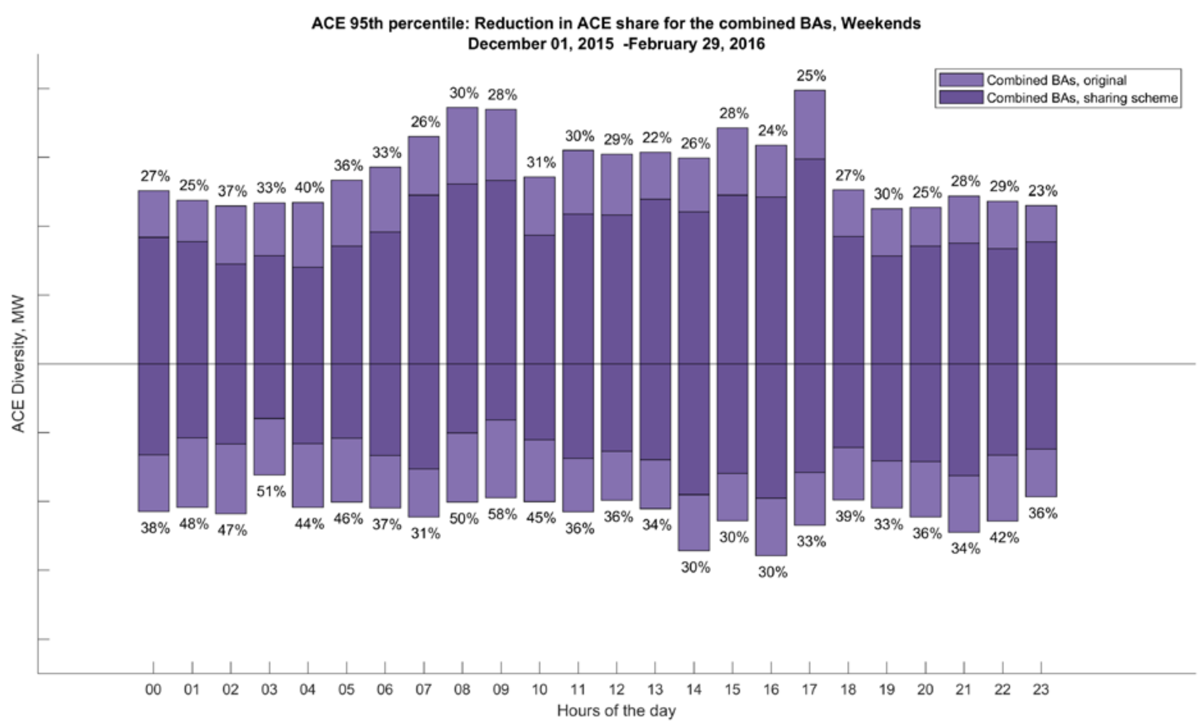

Figure A-28: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekends in December 2015-February 2016.

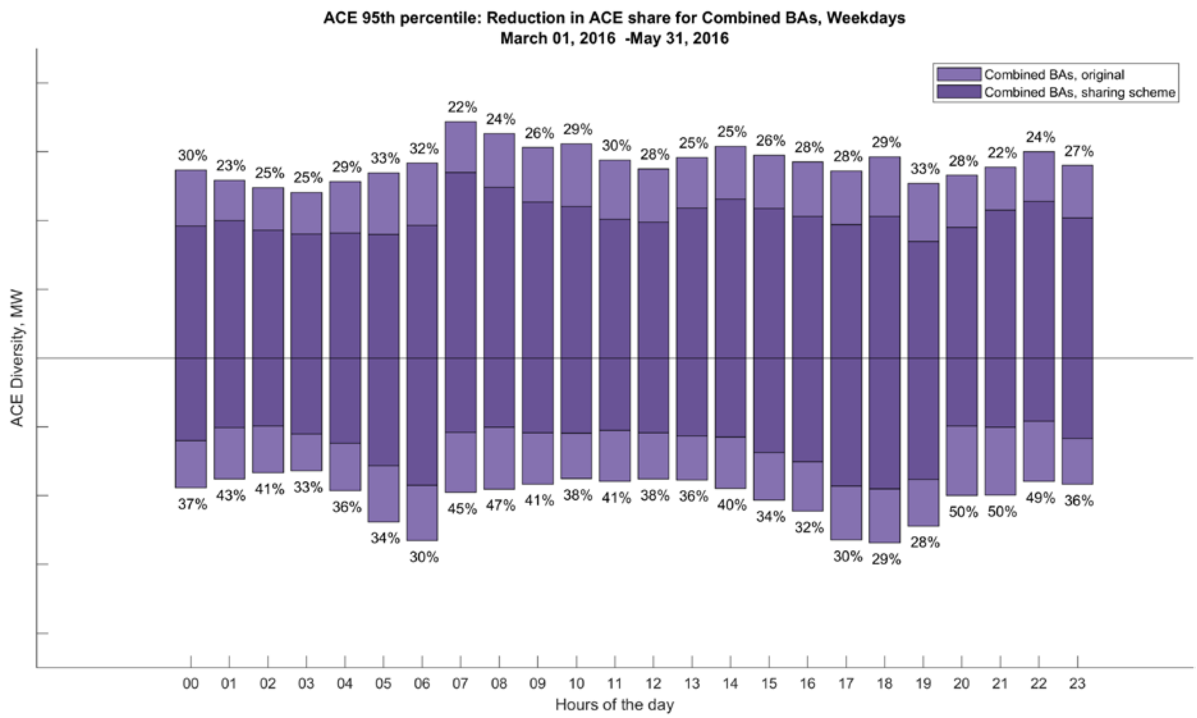

Figure A-29: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in March-May 2016.

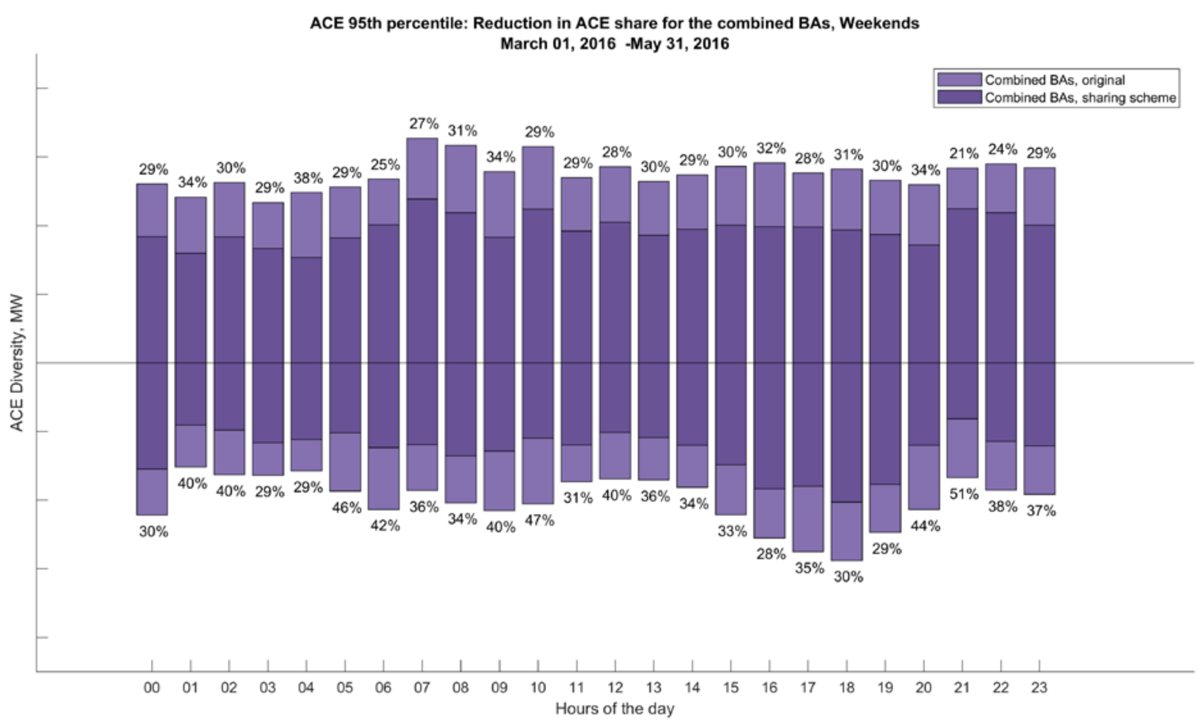

Figure A-30: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekends in March-May 2016.

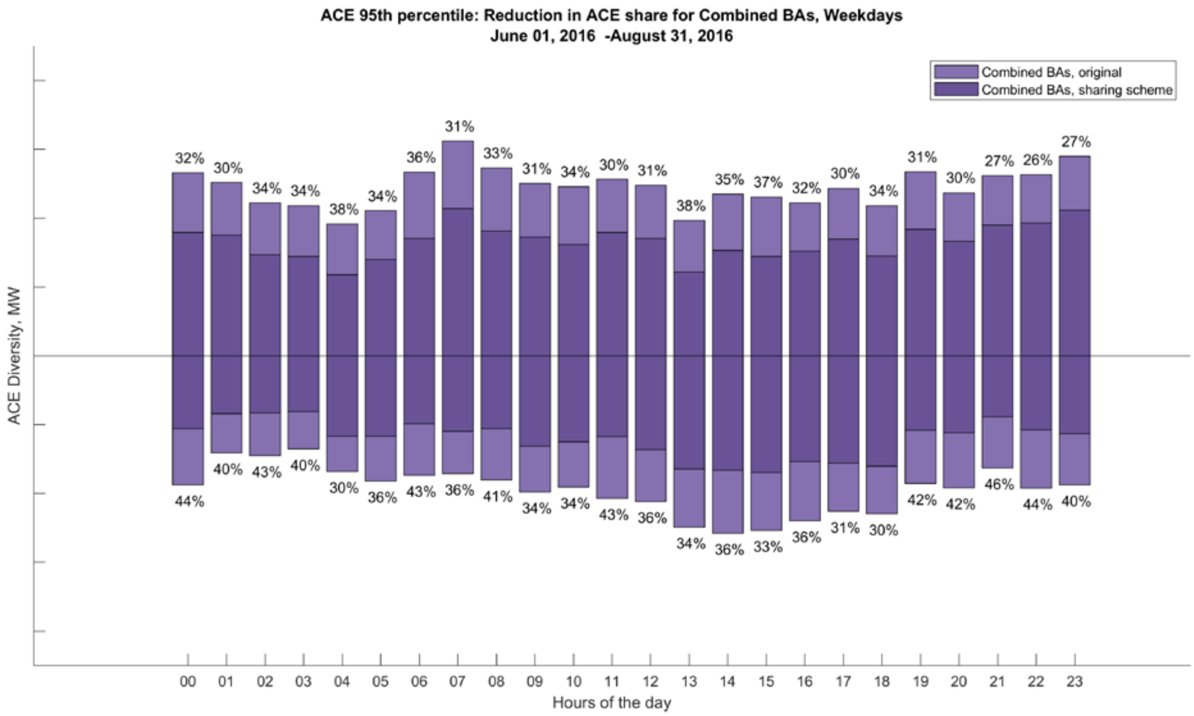

Figure A-31: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in June-August 2016.

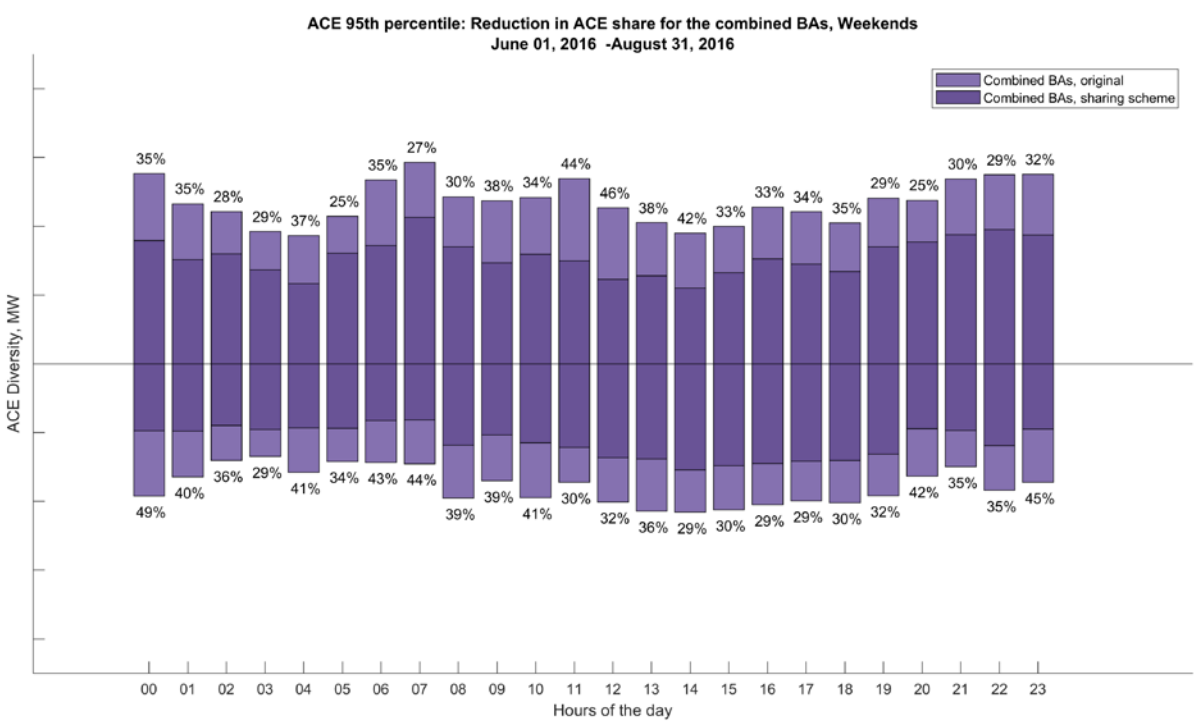

Figure A-32: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekends in June-August 2016.

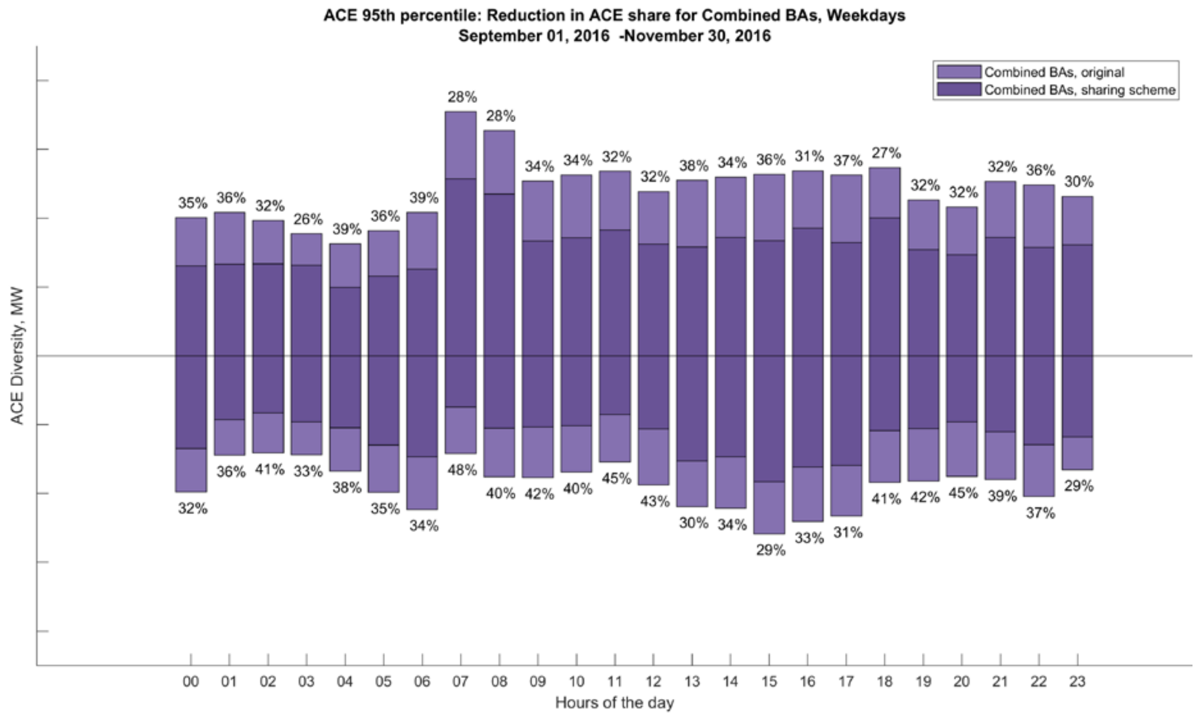

Figure A-33: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in September-November 2016.

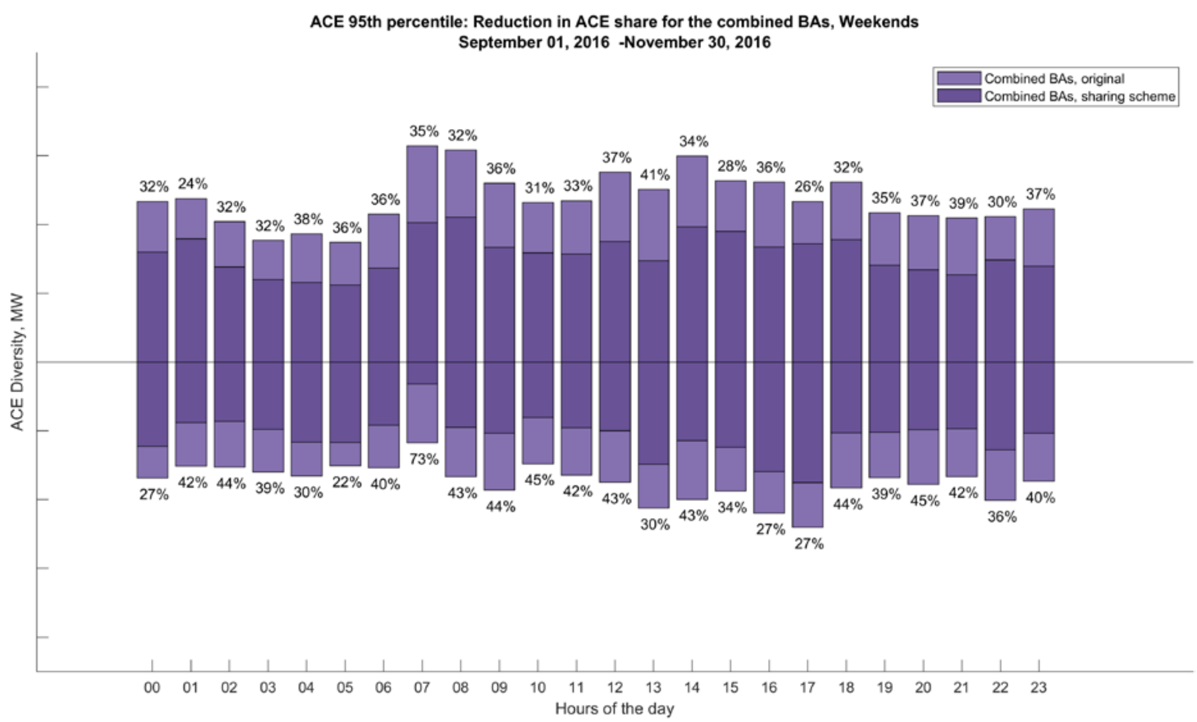

Figure A-34: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekends in September-November 2016.

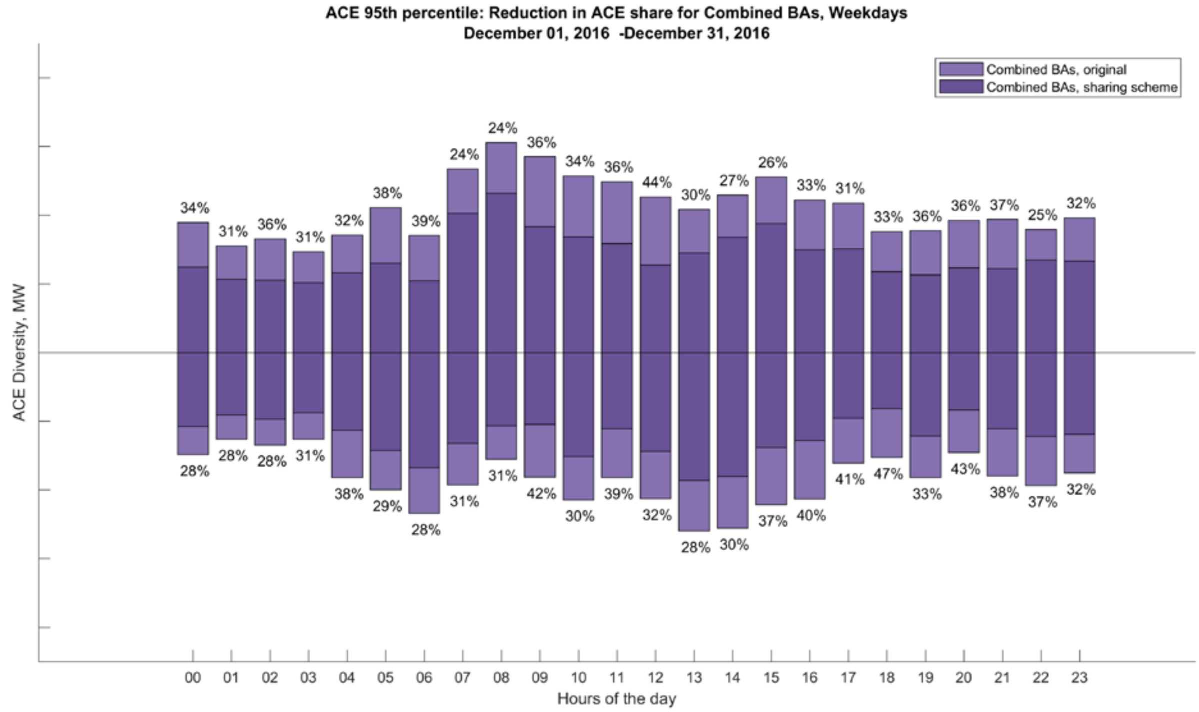

Figure A-35: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in December 2016.

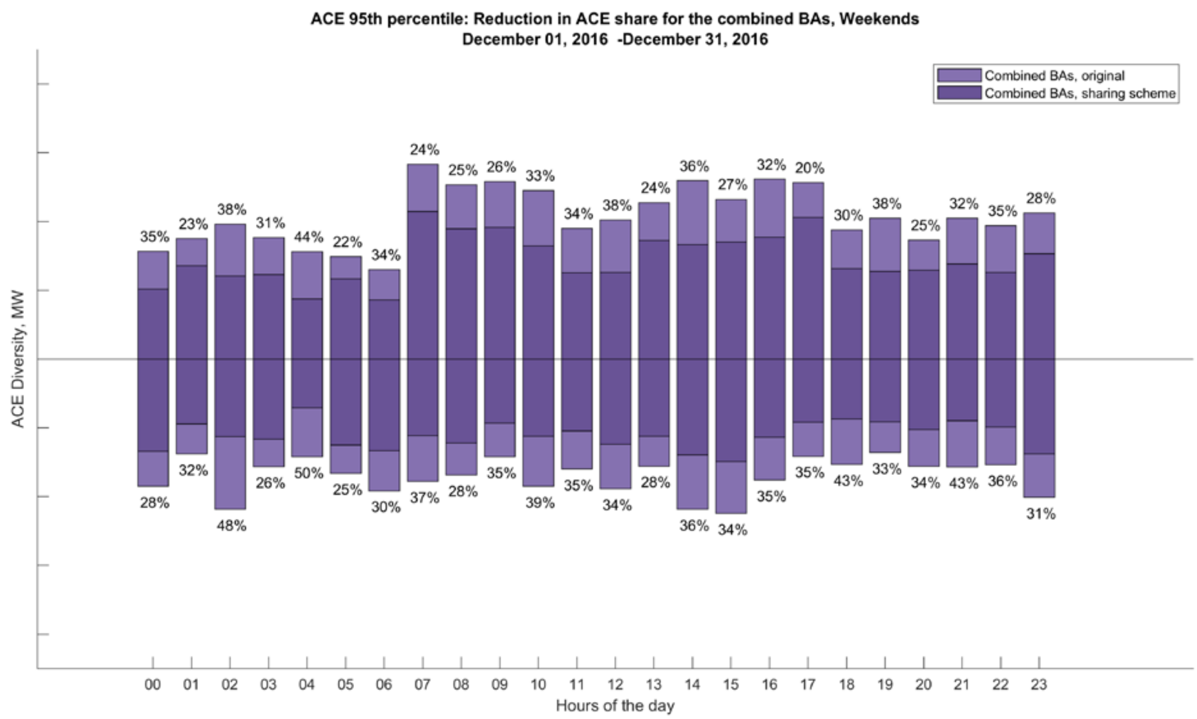

Figure A-36: Reduction in share of ACE variability (95th percentile) responsibility for the combined BAs, for weekdays in December 2016.

Appendix B Analytical Methods

The manuscript in this appendix may be updated for submission to a future technical conference.

Evaluating Predictability of Interconnect Frequency Deviations Using Decomposition-based Automatic Time Series Forecasting

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***Abstract*— This paper presents a study applying decomposition-based automatic time series forecasting methods of uncertainty reduction to a frequency deviation time-series data for the WECC interconnect, using California Independent System Operator (CAISO) data to investigate the predictability of frequency deviations in look-ahead windows ranging from 5 to 10 minutes. Known days with high renewable generation variability and control performance challenge were analyzed alongside "stable" days for comparison. The impacts of the data resolution and the length of training periods were examined with predominantly 1-minute averaged data and with some comparison to original 4-second SCADA data. The training periods were one hour or 5 hours. Results showed that statistically significant reduction in uncertainty can be achieved up to 10-min ahead. The 5-min ahead predictions may yield an uncertainty reduction of about 50%. In some cases, 1-minute data outperformed 4-second data.**

***Index Terms*—Interconnect frequency, Solar Generation, Wind Generation, Area Control Error, Balancing Authority.**

I. Introduction

Prior to January 2016, a rule of thumb generally held true for the California Independent System Operator (CAISO) that if real-time market prices were stable over the course of a day, the North American Electric Reliability Council (NERC) control performance standard 1 (CPS1) would also be stable during that day, and vice versa. From January 2016 onward, that rule of thumb has no longer held true. At that time, Pacific Northwest National Laboratory (PNNL) was undertaking an investigation into multifaceted barriers to increased solar penetration for the Soft Costs program of the Department of Energy's SunShot Initiative [1]. Events experienced by the CAISO from January 2016 onward have shown that when the substantial amount of solar generation in the CAISO service area changed both unexpectedly and by a large-enough quantity in a short-enough time frame, in some cases those changes did not impact the real-time market energy prices even though they still impacted CPS1 1-minute scores, and that the swings in total generation can happen rapidly enough to be invisible to the unit commitment and security-constrained economic dispatch runs. For the first time, the rule of thumb (that stable prices meant stable CPS1 scores and vice versa) no longer held true.

Rather than being an interesting but rare occurrence, this new phenomenon is a continuing and increasing problem: In 2017, the CAISO energy system experiences significant challenges caused by the dramatic growth of renewable grid connected generation (in particular solar generation, e.g., the new peak of grid connected solar production was set at 9,914 MW in June 2017). In addition, penetration of distributed energy resources has been steadily increasing and reached approximately 6,000 MW by the end of 2017. As a result of this unprecedented growth, the CAISO encounters multiple

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critical and interrelated issues that are not easily resolved. These issues include 1) some instances of negative energy prices in the day-ahead (DA) market and frequent negative prices in the real-time (RT) market (for instance, the DA prices were negative over 50 hours total and the RT prices were negative for more than 10% of the time during the first quarter in 2017), 2) lack of balancing capacity and spikes in regulation procurement prices, and 3) deteriorating control performance indexes (required by NERC Reliability standards) [2].

As a preliminary exercise to check whether time-series forecasting tools could produce enough predictability of system variables to be used in real-time operational tools that would address these rapid solar swings in the <10 minute timeframe, PNNL applied time-series forecasting to frequency deviations from scheduled frequency for selected days in January 2016. This paper presents the methodology and initial results for the selected days in January 2016, and for two additional days in March 2017. The purpose of the study reported here was to serve as a preliminary test to see whether a family of approaches using decomposition-based automatic time series forecasting on signals in which frequency is a component could even be workable in the operational timeframe mentioned; as such it does not attempt to solve the complex interrelated problems described. The results are encouraging for this type of approach in this timeframe, which is why those results are reported here.

II. DATA

The Western Interconnect frequency data were supplied by the CAISO, which supplied time series for both interconnect scheduled frequency and interconnect actual frequency. The primary focus is on a time-resolution of one minute, for which the actual frequency values are 1-minute averages of 4-second Supervisory Control and Data Acquisition (SCADA) data. Some additional results are shown using the original 4-second SCADA data.

Early tests on different time periods and different training periods showed that the training period needs to be kept to a few hours or less to provide usable results in the <10 minute time frame. This is a natural consequence of the method described below, which looks back and ahead in terms of numbers of timesteps. As a result, individual days were chosen for the analysis and results presented here. An initial day of interest was chosen in January 2016, since it was the day on which the phenomenon described in the introduction was first noted and was a windy/rainy day during which total solar generation for the CAISO was swinging significantly in <10 minute timeframe and CPS1 hourly scores dropped below 100%. A nearby "stable" day in January 2016 was chosen for comparison. For comparison, another pair of dates were chosen from March 2017; a windy day with patchy rain, producing highly variable wind and solar production, was chosen and a "stable" day was added for contrast.

III. METHODOLOGY

Uncertainty in the frequency deviations can be reduced using accurate short-term forecasting techniques such as the autoregressive integrated moving-average (ARIMA) model. It is generally referred to as an ARIMA(p,d,q) model in which p, d, and q are non-negative integers that refer to the order of the autoregressive, differencing, and moving average parts of the model, respectively. The ARIMA(p, d, q) model of time series $\{y_1, y_2, \ldots, y_n\}$ is defined as

$$\Phi_p(\mathrm{B})\Delta^d \mathrm{y}_t = \Theta_q(\mathrm{B})\epsilon_t\ , \tag{1}$$

where B is the backward shift operator, Δ is the backward difference, d is the order of differencing, y_t are the observational time series (e.g., frequency deviations), and Φ_p and Θ_q are polynomials of orders p and q, respectively.

However, the frequency of an interconnect is not a simple signal to analyze, since it is impacted by the behaviors of many types of load, many types of generation, switching events, and other disturbances. These different impacts can move at dramatically different time scales, such as a switching event occurring in milliseconds versus the ramping-up of a generator taking place over the course of hours. When the time series of interest is a mixture of signals with dramatically different variations at different temporal scales, ARIMA fitting can become difficult or meaningless [3-4].

Time series decomposition can help alleviate this issue. Decomposed components of a time series (e.g., deviations from scheduled frequency, referred to here as Δ-frequency) are expected to have stronger continuity and more consistent autoregressive patterns, which make ARIMA prediction more applicable. With the auto.arima function in the R package 'forecast', the parameters p, d, and q can be automatically trained for each component. Generally, higher-frequency components need an ARIMA model with a larger autoregressive parameter p, while lower-frequency signals require a larger differencing parameter d and moving average parameter q [5-8].

The automated-ARIMA integrated with signal decomposition helps alleviate the non-normality and non-stationarity issues such that ARIMA is more applicable. The ARIMA model parameters are trained automatically using maximum likelihood estimation approach. The original time series are decomposed into three parts: trend, seasonal and random, each component has better autoregressive patterns than the original time series. The overall prediction is:

$$\hat{y} = \hat{y}_{trend} + \hat{y}_{seasonal} + \hat{y}_{random}, \quad (2)$$

With the standard deviation of the prediction approximated as:

$$\hat{s} = \sqrt{\{\hat{s}^2_{trend} + \hat{s}^2_{seasonal} + \hat{s}^2_{random}\}}, \quad (3)$$

and the predictive bounds are approximated as [$\hat{y}$–1.96 $\hat{s}$, $\hat{y}$+1.96 $\hat{s}$].

There are different ways of defining uncertainty in the forecast errors, here we use 1-sum.square(residuals) / sum.square(original) to represent the amount of uncertainty reduced by the predictions.

Systematic time series decomposition and ARIMA model training and forecasting are done for various combinations of system conditions, lengths of training periods, time resolutions, and for different look-ahead time windows, to fully evaluate the performance of the integrated approach and quantify the predictability of the frequency deviation data.

IV. RESULTS

Results for predictions of Δ-frequency using 1-minute and 4-second resolution frequency data (actual, scheduled, and differences) for the Western Interconnect in January 2016 and March 2017 are shown in Figures 1-4 and in Tables 1-2. Besides the comparison of the impacts of data resolution on the predictability of Δ-frequency, we also look at the impact of the length of the training periods, and evaluate the predictability during bad days (e.g., with strong anomalies) and good days. Among the testing cases, the “stable” days are January 26, 2017 and March 5, 2017, and the bad days are January 31, 2016 and March 6, 2017.

A. January 26 and January 31, 2016

Figure 1 shows the decomposition-based ARIMA results with one-minute data and a 5-hour training period for January 26, 2016. The original Δ-frequency is the black line, while the prediction is shown by the red line. The blue and green lines show the upper and lower bounds, respectively. The same information is shown in Figure 2 for January 31, 2016.

Table I gives the amount of uncertainty reduction for different combinations of time resolution and training interval for January 26 and January 31, 2016. The first four lines of the table show the results for one-minute resolution of Δ-frequency. For January 26 and for a one-minute resolution and a one-hour training period, the amount of uncertainty reduction was 46.64% for a 5-minute look-ahead window, 18.69% for a 7-minute look-ahead window, and 9.12% for an 8-minute look-ahead window. For look-ahead windows of 9 and 10 minutes, there was no uncertainty reduction. These results were improved by changing to a 5-hour training period, for which the amount of uncertainty reduction was 52.21% for a 5-minute look-ahead window, 36.28% for a 7-minute look-ahead window, 31.02% for an 8-minute look-ahead window, 24.79% for a 9-minute look-ahead window, and 17.83% for a 10-minute look-ahead window.

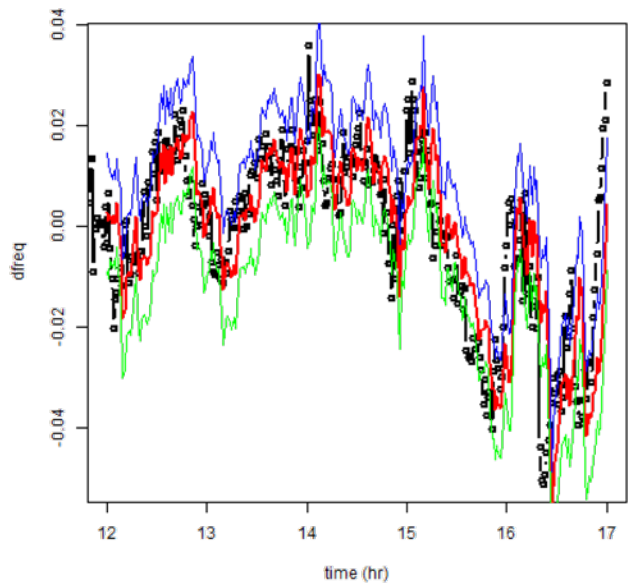

Figure 1. Decomposition-based ARIMA 5-min-ahead prediction of Δ-frequency on January 26, 2016, with 1-min data resolution and 5-hour training period. The black line is the actual Δ-frequency, the red line is the prediction, and the blue and green lines are the upper and lower bounds respectively.

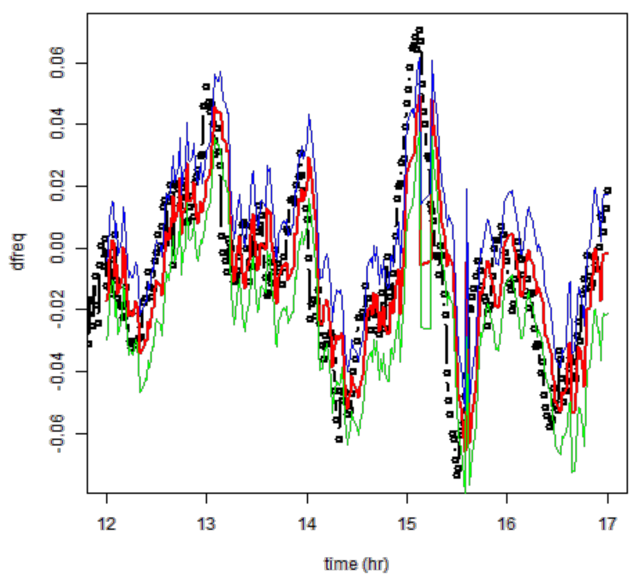

Figure 2. Decomposition-based ARIMA 5-min-ahead prediction of Δ-frequency on January 31, 2016, with 1-min data resolution and 5-hour training period. The black line is the actual Δ-frequency, the red line is the prediction, and the blue and green lines are the upper and lower bounds respectively.

TABLE I. PERCENTAGE UNCERTAINTY REDUCTION, JANUARY 26 VS. JANUARY 31, 2016

data and training interval	5-min	7-min	8-min	9-min	10-min
1-Min, Jan 26 2016, 1-hr training	46.64	18.69	9.12	--	--
1-Min, Jan 26 2016, 5-hr training	52.21	36.28	31.02	24.79	17.83

1-Min, Jan 31 2016, 1-hr training	45.47	4.12	--	--	--
1-Min, Jan 31 2016, 5-hr training	47.76	32.73	24.35	14.29	4.69
4-Sec, Jan 26 2016, 1-hr training	30.43	15.11	10.88	0.89	--
4-Sec, Jan 31 2016, 1-hr training	42.25	19.46	8.95	--	--
4-Sec, Jan 26 2016, 5-hr training	28.71	13.45	9.21	--	--
4-Sec, Jan 31 2016, 5-hr training	42.37	19.52	9.01	--	--

The corresponding values for reduction in uncertainty were lower for January 31, 2016. For a one-minute resolution and a one-hour training period, the amount of uncertainty reduction was 45.47% for a 5-minute look-ahead window and 4.12% for a 7-minute look-ahead window. For look-ahead windows of 8, 9 and 10 minutes, there was no uncertainty reduction. This is substantially lower than the corresponding values for January 26. These results were improved by changing to a 5-hour training period, for which the amount of uncertainty reduction was 47.76% for a 5-minute look-ahead window, 32.73% for a 7-minute look-ahead window, 24.35% for an 8-minute look-ahead window, 14.29% for a 9-minute look-ahead window, and 4.69% for a 10-minute look-ahead window. Again, these values are substantially lower than the corresponding values for January 26, though the longer training interval for January 31 makes the results for that day slightly better than the results of January 26 with the shorter training interval. This would indicated that further investigation of the optimal training window is warranted.

Interestingly, the results for January 31 were better than the results for January 26 for shorter look-ahead windows when the time resolution of Δ-frequency was changed to 4 seconds instead of 1-minute averages of 4-second data. For a four-second resolution, a one-hour training period, and a 5-minute look-ahead window, the amount of uncertainty reduction was 30.43% for January 26 and 42.25% for January 31; for a 7-minute look-ahead window, the amount of uncertainty reduction was 15.11% for January 26 and 19.46 for January 31; however for an 8-minute look-ahead window the amount of uncertainty reduction was 10.88% for January 26 and 8.95 % for January 31. Similarly, for a four-second resolution, a one-hour training period, and a 5-minute look-ahead window, the amount of uncertainty reduction was 28.71% for January 26 and 43.37% for January 31; for a 7-minute look-ahead window, the amount of uncertainty reduction was 13.45% for January 26 and 19.52 for January 31; however for an 8-minute look-ahead window the amount of uncertainty reduction was 9.21% for January 26 and 9.01 % for January 31. So with 4-second data, January 31 performed better than January 26 for shorter look-ahead windows for both 1-hour and 5-hour training periods.

Note that 4-second data did not necessarily give an advantage over 1-minute averaged data for look-ahead windows of the lengths chosen, and often produced lower results. The time-series methods used function best for smaller number of timesteps in the look-ahead windows. At these time scales the advantage of having a smaller number of timesteps by using averaged data has the advantage over finer resolution data with more timesteps per minute.

B. March 5 and March 6, 2017

Only 1-minute time-resolution data was looked at for March 5 and March 6, 2017. Figure 3 shows the decomposition-based ARIMA results with one-minute data and a 5-hour training period for March 5, 2017. The original Δ-frequency is the black line, while the prediction is shown in the red line. The blue and green lines show the upper and lower bounds, respectively. The same information is shown in Figure 4 for March 6, 2017.

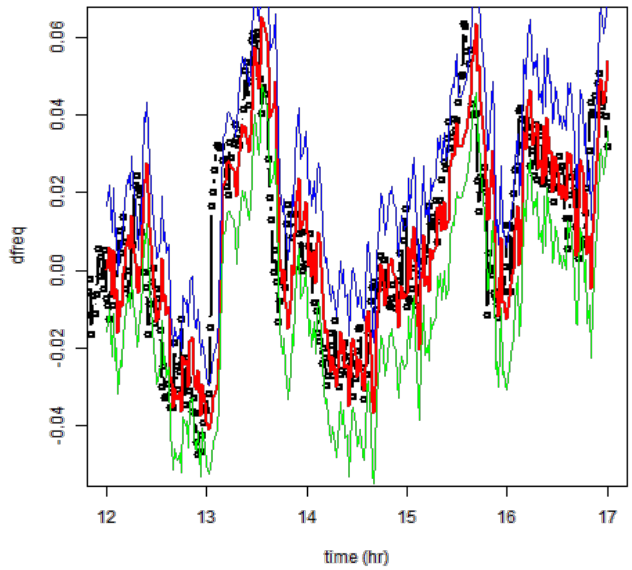

Figure 3. Decomposition-based ARIMA 5-min-ahead prediction of Δ-frequency on March 5, 2017, with 1-min data resolution and 5-hour training period. The black line is the actual Δ-frequency, the red line is the prediction, and the blue and green lines are the upper and lower bounds respectively.

Table II gives the amount of uncertainty reduction for different combinations of time resolution and training interval for March 5 and March 6, 2017. For March 5 and for a one-minute resolution and a one-hour training period, the amount of uncertainty reduction was 48.14% for a 5-minute look-ahead window, 18.17% for a 7-minute look-ahead window, and 0.59% for an 8-minute look-ahead window. For look-ahead windows of 9 and 10 minutes, there was no uncertainty reduction. These results were improved by changing to a 5-hour training period, for which the amount of uncertainty reduction was 55.40% for a 5-minute look-ahead window, 40.68% for a 7-minute look-ahead window, 31.92% for an 8-minute look-ahead window, 23.61% for a 9-minute look-ahead window, and 15.82% for a 10-minute look-ahead window.

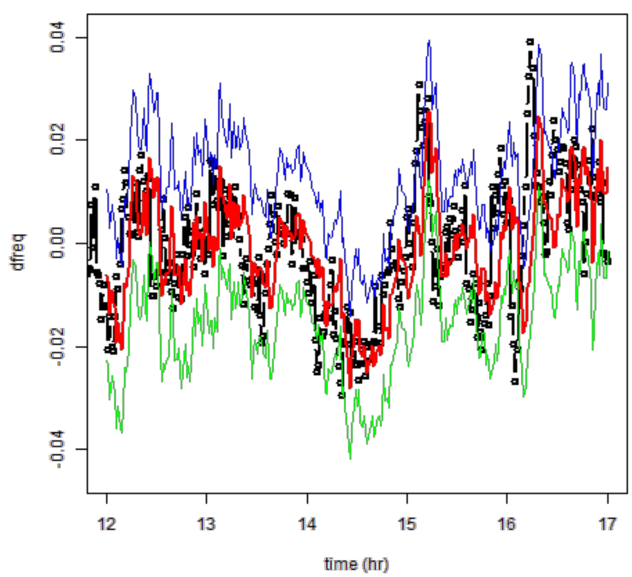

Figure 4. Decomposition-based ARIMA 5-min-ahead prediction of Δ-frequency on March 6, 2017, with 1-min data resolution and 5-hour training period. The black line is the actual Δ-frequency, the red line is the prediction, and the blue and green lines are the upper and lower bounds respectively.

TABLE II. PERCENTAGE OF UNCERTAINTY REDUCTION, MARCH 5 VS. MARCH 6, 2017

data and training interval	5-min	7-min	8-min	9-min	10-min
1-Min, Mar 5 2017, 1-hr training	48.14	18.17	0.59	--	--
1-Min, Mar 5 2017, 5-hr training	55.40	40.68	31.92	23.61	15.82
1-Min, Mar 6 2017, 1-hr training	8.58	--	--	--	--
1-Min, Mar 6 2017, 5-hr training	13.56	--	--	--	--

The corresponding values for reduction in uncertainty were much lower or nonexistent for March 6, 2017. For a one-minute resolution and a one-hour training period, the amount of uncertainty reduction was 8.58% for a 5-minute look-ahead window, with no measurable uncertainty reduction for the larger look-ahead windows. These results were somewhat improved by changing to a 5-hour training period, for which the amount of uncertainty reduction was 13.56% for a 5-minute look-ahead window, with no measurable uncertainty reduction for the larger look-ahead windows. Of the days considered, March 6, 2017 is the most difficult to predict due to its fast and continuously changing variance and periodicity).

Overall, March 5, 2017 and January 26, 2016 are the two days with relatively consistent autoregressive patterns, although the latter has strong anomalies between 16:00-17:00.

V. CONCLUSIONS

An automated decomposition-based time series forecasting approach was developed and successively tested on Western interconnect frequency data from the CAISO. The approach was used to systematically explore the predictability of frequency deviations in the system under various system conditions (e.g., corresponding to different problematic renewable generation performance and control performance). Such predictability, in terms of the amount of reduced uncertainty, were summarized with respect to the data resolution and the length of training periods, with considered look-ahead windows ranging from 5 to 10 minutes. In general, statistically significant reduction in uncertainty can be achieved up to 10-min ahead, using 5-hour training period, which outperforms the 1-hour training period with a prediction range of 8-min ahead. Short-term predictions (e.g., 5-min ahead) may result in up to 50% uncertainty reduction, and 1-minute data seems to be adequate for the case studies as it often outperformed 4-second data.

The approach performed well for the two time periods of study which were chosen as “stable” days when the weather and other major impacts on the system were fairly quiet, as well as for the unstable time period which was the day that originally prompted this study. For a time period featuring wind and patchy rain, however, white noise dominated the signal at the time resolution and look-ahead windows considered; therefore, while some uncertainty reduction was achieved, it did not compare to the other time periods. The approach performing well on the “stable” days and the day dominated by wide solar swings were enough to investigate this type of approach further for solutions that could help with the problems described in the introduction for the CAISO.

The substantial changes in the amount of uncertainty reduction when changing between 1-hour and 5-hour training periods indicates that further fine-tuning of the training period is warranted. Too long a training period would involve the system state and the weather being able to change too much over the training period interval, and too short a training period would not train the method sufficiently.

Prediction using data of 4-second time resolution performed equally or even worse than corresponding results for 1-minute data. For the look-ahead windows considered, the increased number of timesteps in going to 4-second resolution made the total number of timesteps too large to produce much uncertainty reduction using these methods, with the result that 1-minute data had a distinct advantage given its computational efficiency.

Future work will include fine-tuning the model parameters with longer records of data (e.g., along the course of a year), as well as comparison with other advanced time series forecasting techniques that are recently developed (e.g., auto-encoder or the short and long term memory (LSTM) deep learning approach).

Additional future work will involve re-examining the results of tests of the sort that are detailed here every few years for each/any major interconnect. The overall load profile, including the predominance of electronic load, has undergone dramatic change and will continue to change, while new types of renewable and distributed resources and new types of controllers come available. The change in balance of these factors over time or between interconnects warrants re-examining how well certain approaches to analyzing interconnect frequency work under existing conditions.

The two broadest conclusions are: 1) This type of approach over the operational timeframe given and in 2016-2017 conditions for the Western Interconnect worked well for frequency deviations and therefore might work well for other operational signals of which frequency is a component; and 2) preliminary tests of such methods under different conditions can be performed as detailed here. The results are strong enough to warrant further consideration of such methods for the phenomena plaguing the CAISO described in the introduction.

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