Value of Distribution-Level Reactive Power for Combined Heat and Power Systems

by

Monica Harnoto
B.S., Environmental Sciences, University of California, Berkeley, 2013

Submitted to the MIT Sloan School of Management and MIT Department of Civil and Environmental Engineering in partial fulfillment of the requirements for the degrees

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Abstract

As the U.S. electric grid continues to experience an increase in the penetration of distributed energy resources (DER), electric utilities are evaluating new approaches for utilizing DER to help cost-effectively maintain grid resilience and reliability. One such approach is to create a transactive market for DER to provide grid services, which are services required to support reliable grid operation. Though work has been done to understand some of the technical mechanisms of this type of market, gaps still exist in understanding the value and market opportunity of ancillary services at the distribution level.

One type of ancillary service – reactive power – is of particular interest because of the theoretic ability to source from existing assets on the distribution network. This paper aims to build understanding of the value of procuring reactive power from one of these assets: Combined Heat and Power (CHP) systems. The value of procuring reactive power from a CHP system will be quantified by 1) characterizing CHP systems' capacity to produce and absorb reactive power, 2) assessing the annual cost of procuring reactive power from CHP systems, and 3) comparing the CHP system technical capability and cost to the utility's conventional solution: capacitor banks.

This study finds that, while there are promising scenarios in which CHP systems can technically and economically provide reactive power in a comparable or slightly advantaged manner to capacitor banks, the overall statistics for the 29 CHP systems analyzed in the New York fleet do not conclusively demonstrate an advantage that supports outright replacement of capacitor banks. Further assessment of CHP systems as a complementary source of reactive power and site-specific case studies are recommended to inform the next step in the decision making process for determining whether this path should be pursued as a source of reactive power.

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List of Acronyms

AR	Autoregression
ARIMA	Autoregressive Integrated Moving Average
CHP	Combined Heat and Power
DER	Distributed Energy Resource
DSP	Distributed System Platform
HHV	Higher heating value
I	Differencing
MA	Moving Average
NWA	Non-Wires Alternative
NY REV	New York Reforming the Energy Vision
NYISO	New York System Operator
NYSERDA	New York State Energy Research and Development Authority
PV	Photovoltaic
RMSE	Root Mean Square Error
SARIMAX	Seasonal Autoregressive Integrated Moving Average with eXogenous Regressors
SVC	Static VAR compensator
VA	Volt-Ampere
VAR	Volt-Amperes Reactive

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List of Symbols

$a_{s,CHP}$	CHP system availability for a given site
c_{CB}	Capital cost of the capacitor bank ($)
b	Site
B	Total number of sites
d	Order of differencing used
D	Order of seasonal differencing used
$e_{s,CHP}$	Total energy produced for a given site (kWh)
$EAC_{Q,CB,kVAR}$	Equivalent annual cost of reactive power from a capacitor bank based on capacity ($/year/kVAR)
$EAC_{Q,CB,kVARh}$	Equivalent annual cost of reactive power from a capacitor bank based on total reactive power produced ($/year/kVARh)
$EAC_{Q,CHP,kVAR}$	Equivalent annual cost of reactive power from CHP system based on capacity ($/year/kVAR)
$EAC_{Q,CHP,kVARh}$	Equivalent annual cost of reactive power from CHP system based on total reactive power produced ($/year/kVARh)
f	Fuel cost ($)
i	Number of exogenous variable
I_{CB}	Installation cost of the capacitor bank ($)
L	Lag operator
m	Number of time lags comprising one full period of seasonality
M_{CB}	Maintenance cost of the capacitor bank ($)
n	Maximum number of exogenous variables
P	Real power (kW)
$P_{max,CHP}$	CHP system maximum lagging reactive power output rating (kW)
Q	Reactive power (kVAR)
$Q_{max,CHP}$	CHP system maximum lagging reactive power output rating (kVAR)
$Q_{min,CHP}$	CHP system maximum leading reactive power output rating (kVAR)
Q_b	Total reactive power produced in a year at a given site (kVARh)

$Q_{b,cap}$	Reactive power capacity for a given site (kVAR)
ξ	Number of time lags to regress on for MA term
Ξ	Number of time lags to regress on for seasonal MA term
r	Weighted average cost of capital (%)
S	Apparent power (kVA)
t	Time
t_{CB}	Expected life-span of capacitor bank (years)
$t_{b,CHP}$	Total hours included in a dataset (hours)
x_t^i	Exogenous variables for $i \leq n$ at time t
y_t	Time series (kVAR)
$z_{s,CHP}$	Total number of hours where zero power was produced for a given site (hours)
β_i	Coefficient estimated by model for exogenous variables for $i \leq n$
Δ^d	Integration operator where $y_t^{[d]} = \Delta^d y_t = y_t^{[d-1]} - y_{t-1}^{[d-1]}$
Δ_m^D	Integration operator for seasonal differences
ε_t	Noise at time t (kVAR)
$\theta(L^m)^P$	An order P polynomial function of seasonal L^m
$\Theta(L)^p$	An order p polynomial function of L
ξ	Number of time lags to regress on for MA term
Ξ	Number of time lags to regress on for seasonal MA term
$\phi(L^m)^Q$	An order Q polynomial function of seasonal L^m
$\Phi(L)^q$	An order q polynomial function of L
Ψ	Number of time lags to regress on for AR term
ψ	Number of time lags to regress on for seasonal AR term

Chapter 1 – Introduction

This paper aims to provide an assessment of the potential value of reactive power sourced from CHP systems. Chapter 1 describes the motivation for the project, defines the problem statement that is being addressed, and outlines the initial hypothesis and research approach. The chapter concludes with a discussion of the paper's major contributions, project scope and limitations, and an outline of the organization of this thesis.

1.1 Project Motivation

DERs have become increasingly prevalent on the U.S. electric grid. According to the 2019 Annual Outlook Report, the U.S. Energy Information Administration expects residential solar photovoltaic (PV) capacity to increase by an average of 8%, commercial PV capacity to increase by 5%, and non-PV DER technologies like wind and CHP to increase by 4-5% by 2050 [1]. The report also notes tax credits available to both PV and non-PV DER technologies that decrease life cycle cost and are expected to drive further adoption through 2022. The growth in DER has been driven in part by a number of potential benefits, including grid resiliency, energy security, fuel diversity, and market efficiency [2]. However, to realize these benefits, the electric power system must create new methods to manage the complexities introduced by large DER adoption.

Though the DER category encompasses a broad range of technologies, the distributed and oftentimes intermittent nature of these technologies presents similar challenges across the category. These challenges persist through grid operation, planning, and market design [2], [3]. Operationally, coordination becomes increasingly challenging as the number of interconnection points increases. System operators must ensure the optimal production of sufficient power generation across an increasingly large number of power generation units, which requires increasingly complex modeling and coordination.

Capacity and infrastructure planning also becomes more complex as models must incorporate the impact of DERs on the capacity, availability, reliability, and power flow of a given area. Planning for sufficient capacity must account for the extreme situations of zero and maximum DER production [4]. In addition to these extremes, efficient capacity procurement must also incorporate some level of understanding of the availability and reliability of the DERs. This understanding helps capacity planners balance the need to maintain reliable power with a larger number of potential points of failure while minimizing system cost. The direction of the power flow also influences the infrastructure build requirements. As opposed to the centralized power generation system where power largely flows unidirectionally from a large power plant to the end user, DERs introduce points at which power can flow from the end user back to the substation [2].

Finally, compensation for DERs becomes more challenging as grid operators consider utilization of DERs beyond conventional behind-the-meter self-consumption. Though market mechanisms exist to compensate power plants to reliably meet power demand with supply, these markets have largely been built around the centralized power generation paradigm. Certain aspects of the market may still work to compensate DERs for grid services. However, there are sufficient differences in their capacities, locational specificity, and reliability and availability characteristics to indicate the need for different compensation schemes to incentivize efficient operation.

One state that has expended significant effort to start grappling with the challenges outlined above is New York [2]. New York’s Reforming the Energy Vision (NY REV) outlines the state’s comprehensive strategy for transitioning to a clean, resilient, and affordable energy system [5]. In alignment with NY REV, the New York Independent System Operator (NYISO) stated in its 2019 Power Trends report that they are in the midst of a multi-year effort that will open New York’s wholesale Energy, Ancillary Services, and Capacity Markets to DER technologies with a goal to set rules for DER integration and implementation by 2021 [6]. The NYISO has also initiated a pilot project program to test frameworks for DER participation in wholesale markets. The program has a number of stated goals, but the goal that is of particular interest for this paper centers on demonstrating coordination processes and procedures between the ISO and the Utilities’ Distributed System Platform (DSP) [7].

According to this vision, the DSP will provide the mechanism through which utilities conduct integrated system planning, grid operations, and market operations. Integrated system planning will expand beyond its current focus on capital planning to include investments that enable the development of DER investments. Grid operations will similarly be required to expand to incorporate inputs from DER through the DSP to maintain a balanced and reliable grid. Finally, market operations will evolve to facilitate retail interactions with the wholesale market and to provide compensation mechanisms for DER that are transparent.

National Grid is one of the utilities that has initiated testing of a DSP through a NY REV demonstration project. The goal of National Grid's BNMC DSP Engagement tool was to:

"…identify the locational generation value of customer-owned distributed energy resources ("DER") and provide a platform that will allow these assets to participate and provide energy and/or ancillary services to the electric distribution system [8]."

Through this initiative, progress has been made to understand the value of procuring energy from DER. National Grid leveraged work completed as part of their Benefit-Cost Analysis Handbook to develop the LMP+D+E model, which was used to generate the price signal for DER compensation [9]. The LMP+D+E compensation model accounted for the energy (LMP), load relief resulting from local energy production (D), and societal benefit (E). However, gaps still exist in understanding the value and market opportunity of distribution-level ancillary services. This paper aims to build understanding by focusing in on the value of one type of ancillary service: reactive power.

1.2 Problem Statement

The value of DER-sourced reactive power can vary depending on the stakeholder, location, and DER technology of focus. As National Grid considers potential expansion opportunities for the DSP, they have started evaluating a DER asset that is already interconnected to their distribution network: CHP systems. This paper will take the perspective of National Grid as they assess the value of procuring reactive power from existing CHP systems in their New York territory. This value will be assessed by quantifying the benefits and costs of procuring reactive power from CHP systems and contrasting that with the quantified benefits and costs of providing reactive power through the utility's traditional solution: a capital investment in a capacitor bank. Specifically, the paper will:

1. Characterize the reactive power export potential and economic cost for CHP systems in New York and
2. Compare reactive power export potential and economic cost to that of a capacitor bank.

1.3 Hypothesis

The value of reactive power export potential from CHP systems is of interest because of its position as an existing asset on the New York distribution network, its ability to control reactive power export or absorption levels, and the theoretical existence of excess capacity. CHP systems are often sized according to the onsite heat load, but operated to follow the load's power needs. The load's actual power needs may not always reach the maximum capacity of the CHP system, leaving room for export of reactive power. If this excess capacity exists in a meaningful amount and reactive power can be produced or absorbed in a predictable manner, CHP systems could be well poised to provide near-term reactive power support to the distribution system.

In order for the distribution system to realize this benefit, the existence of the reactive power capacity and the economic competitiveness of this reactive power source must be proved. This study will investigate both factors.

1.4 Major Contributions

This paper helps to further progress understanding of the potential of reactive power sourced from CHP systems by:

1. Providing a methodology for evaluating state-level technical and economic potential of sourcing reactive power from CHP systems;
2. Creating a framework for comparing technical and economic potential of reactive power sourced from CHP systems to capacitor banks;
3. Developing insights, based on real operational data, that suggest CHP systems do not have the predictability or availability to replace capacitor banks, but could serve as a complement; and
4. Showing analysis that reflects overall CHP system reactive power production cost to generally be comparable to capacitor bank cost.

1.5 Scope and Limitations

Because of the nature of the goals outlined for this study, there are a number of limitations that should be noted. First, this study is not intended to assess value of reactive power broadly, but rather to focus specifically on reactive power sourced from CHP systems with synchronous generators [10]. Because of limitations on appropriate datasets for these types of CHP systems within National Grid's New York Territory, this thesis includes datasets from CHP systems located in the entirety of New York state. As a result, the conclusions drawn in this study are not specific to National Grid's current system, but should be informative for future scenarios in which additional CHP systems are added to the distribution network.

Second, because the goal of this study is to provide guidance from a system-level view, there are a number of simplifying assumptions that were made to allow for processing large amounts of data that contained missing datapoints. This applies to the treatment of both the raw data and modeling techniques. Any simplifying assumptions made in this study are outlined in the methods sections below.

Third, the economic assessment included in this study is based on an assessment of cost, not a valuation of the benefits provided by reactive power. An assessment of appropriate pricing based on these benefits requires a more granular and location-specific assessment that is out of scope for this thesis.

1.6 Thesis Outline

Chapter 2 provides relevant background information for this study. This background includes an overview of reactive power within National Grid's distribution system, discussion of the vision for DSP in New York, and information on CHP systems in New York.

Chapter 3 focuses on the technical characterization of reactive power supply from CHP systems. This section outlines the characteristics of the datasets used, steps taken to prepare the data for the model, and methods for characterizing reactive power at both the individual site and state level. The chapter concludes with the resulting characterization of CHP system reactive power potential and the benchmark comparison to reactive power from capacitor banks.

Chapter 4 looks at the comparative costs associated with sourcing reactive power from CHP systems and from capacitor banks. The section outlines methods for evaluating these costs and provides estimates for both CHP system and capacitor banks.

Chapter 5 provides a summary of the key conclusions, gives recommendations on applications for the findings, and suggests opportunities for future work.

Chapter 2 – Background

This chapter aims to provide the context against which this thesis was written. First, the study discusses the role of reactive power in the distribution system and its conventional sources. Then, it will address the vision for DSP in New York and its relationship with sourcing reactive power from CHP systems. Finally, this section concludes with a discussion on typical CHP system applications and operation.

2.1 Reactive Power in the Distribution System

The electric power system needs two kinds of power to operate: real power (P), which is measured in watts, and reactive power (Q), which is measured in volt-amperes reactive (VAR) [11]. The vector sum of P and Q is apparent power (S), which is measured in volt-ampere (VA). The mathematical relationship, therefore, is: $S^2 = P^2 + Q^2$. Reactive power is present when current leads or lags voltage. Leading reactive power refers to the reactive power that flows as a result of current leading voltage and lagging reactive power as a result of current lagging voltage. Distribution system current tends to lag voltage, due to the presence of inductive loads like motors.

Reactive power flow increases active power losses, takes up capacity on distribution lines and causes the deterioration of voltage conditions in the network [12]. In an ideal world, any requisite reactive power for the electric power system would be supplied directly at the inductive load, or the load that consumes reactive power. Examples of common inductive loads are electric motors and transformers. Production of reactive power directly at the point of consumption would result in unity power factor across the distribution system – in other words, the ratio of real power to apparent power would be 1. However, this is a theoretical maximum and current typically lags voltage in distribution systems. Therefore, leading reactive power can be injected to bring the distribution system's power factor closer to 1.

National Grid's New York territory has both radial and network distribution system designs [13]. Throughout these distribution systems, reactive power is typically managed through the installation of capacitor banks at substations [11], [14], [15]. Though cost effective, static reactive power production is not able to regulate voltage in a way that optimizes for system efficiency – it is either able to provide the set amount of reactive power, or turn off. Dynamic sources of reactive power at the distribution level include Static VAR compensators (SVCs), inverters, and generators. Because of its widespread use, this study will focus on capacitor banks as the benchmark technology against which CHP systems will be compared.

2.2 DSP Vision

National Grid recognizes the central role of utilities in helping New York state achieve its decarbonization goals [16]. One of their main levers for enabling this goal is the integration of distributed generation through the DSP. The New York State Public Service Commission defines the DSP as:

"…an intelligent network platform that will provide safe, reliable and efficient electric services by integrating diverse resources to meet customers' and society's evolving needs. The DSP fosters broad market activity that monetizes system and social values, by enabling active customer and third party engagement that is aligned with the wholesale market and bulk power system [7]."

Two of the main pillars of the DSP vision are to lower the cost of grid infrastructure through non-wires alternatives (NWA) and to maintain safe and reliable operation of the distribution system as more DER connect to the system [16]. As an existing asset on the distribution system, CHP systems presents the possibility of meeting reactive power needs on the network without infrastructure investment. The DSP would enable such transactions to take place if both technical feasibility and economic value proved to be comparatively advantageous to more traditional solutions.

2.3 CHP Systems in New York

According to a 2017 New York State Energy Research and Development Authority (NYSERDA) CHP system baseline assessment, New York has roughly 446 known CHP systems installed with an average system capacity of 2.8 MW [17]. Typical site types for CHP installations include Multifamily Buildings, Educational Institutions, Hotels, Hospitals, Offices, Assisted Living, and Restaurants. NYSERDA's assessment of CHP system penetration by market is described below in Table 2-1. The listed markets are reflective of the types of customers represented in the data sets used in this study.

Table 2-1. NYSERDA's Assessment of CHP system penetration in New York state by market [17]

TARGET MARKET	CHP SYSTEMS INSTALLED (CUMULATIVE) - VENDOR SURVEY		CHP SYSTEMS INSTALLED, 1995-PRESENT		TECHNICAL MARKET POTENTIAL		PENETRATION RATE	
	NUMBER	CAPACITY (MW)	NUMBER	CAPACITY (MW)	NUMBER	CAPACITY (MW)	NUMBER	CAPACITY (MW)
Multifamily Buildings	35	9	120 [46]	63 [7]	2,301	510	5%	12%
Educational Institutions	29	15	78 [14]	156 [45]	1,592	1,011	5%	15%
Hotels	15	5	18 [10]	21 [5]	1,123	442	2%	5%
Hospitals	20	16	26 [12]	38 [26]	227	462	11%	8%
Offices	11	22	23 [9]	26 [14]	5,927	1,290	0.4%	2%
Assisted Living	10	2	41 [7]	11 [2]	547	141	7%	8%
Restaurants	0	0	1 [0]	0.12 [0]	465	57	0.002%	0.002%
Unknown/ Other	26	8	140 [39]	938 [69]	5,184	6,962	3%	13%
Total	146	76	446 [137]	1253 [169]	16,901	10,818	3%	12%

Sources:
1. Vendor data: vendor survey
2. CHP systems installed, 1995-present: U.S. DOE database. Figures in brackets represent data from NYSERDA DG-IDS database
3. Technical market potential: U.S. DOE, *Combined Heat and Power (CHP) Technical Potential in the United States, March 2016*
4. Penetration rate: calculated as CHP systems installed, 1995-present, divided by technical market potential

CHP systems generate power and recover thermal energy for onsite consumption [18]. Figure 2-1 and Figure 2-2 outline the basic processes for two configurations of CHP systems: one driven by a reciprocating engine, microturbine, or gas turbine and one driven by a steam turbine. They are typically sized to match the heat demand of a facility because CHP thermal output efficiency is normally greater than electricity and it is assumed that the redundant electricity can be sold back to the grid [19]. Because of the cost associated with installing a unit onsite, investment in a CHP system typically make sense for sites with a relatively steady baseload power consumption pattern and need for heat.

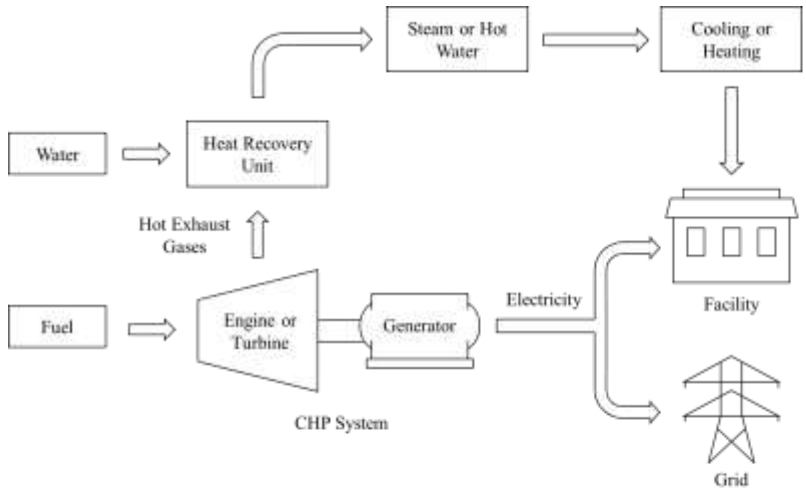


Figure 2-1. Diagram of CHP system with reciprocating engine, microturbine, or gas turbine as prime mover [18], [20]

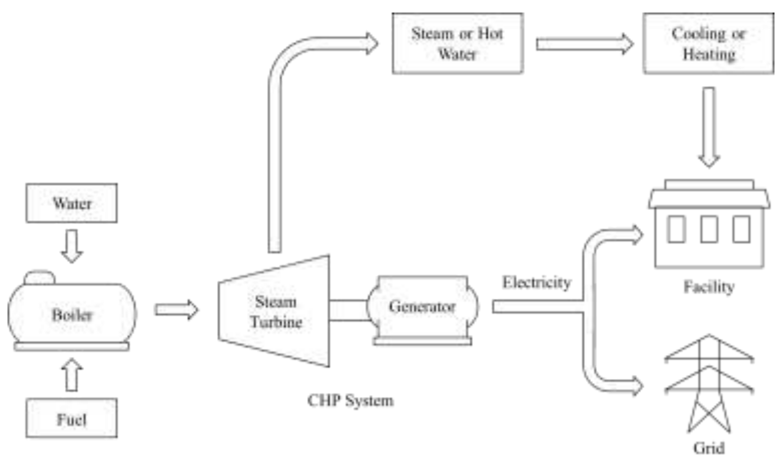


Figure 2-2. Diagram of CHP system with steam turbine as prime mover [18]

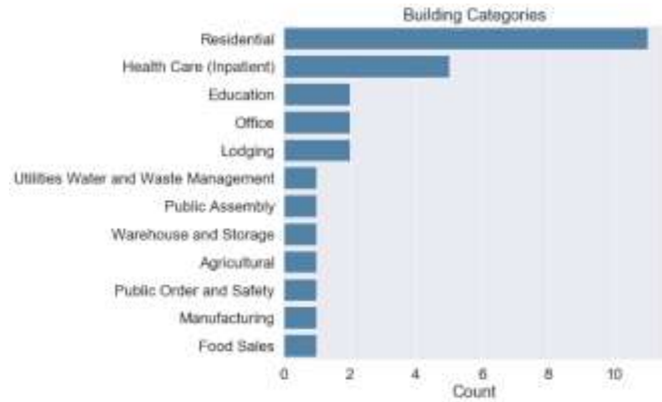
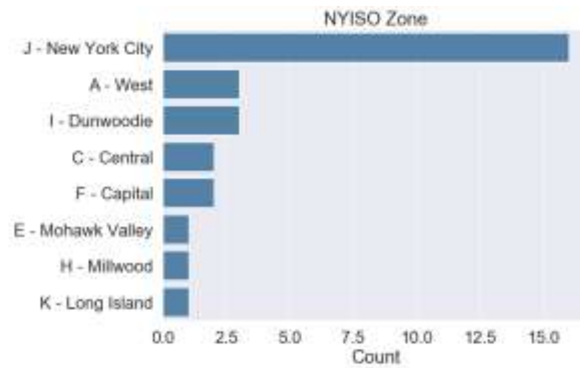
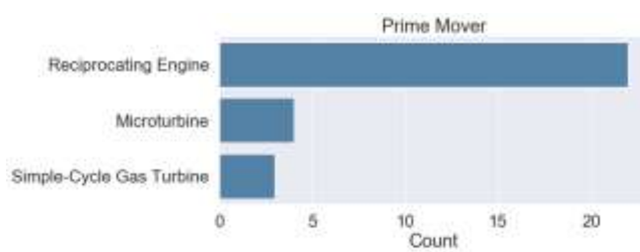
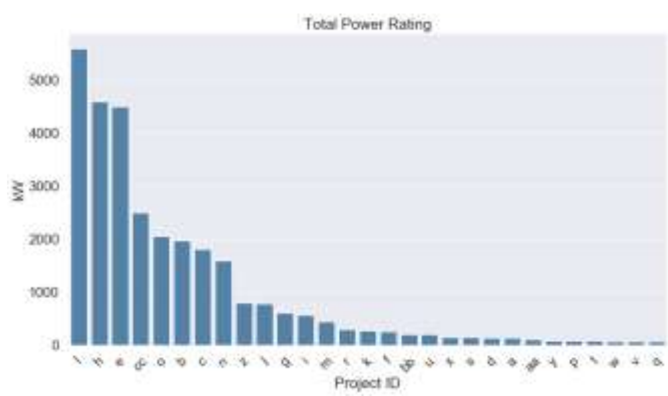
Chapter 3 – Characterizing Reactive Power Potential for CHP Systems

Each building's electrical consumption is unique. Furthermore, electrical consumption can vary for a given building across different time scales – Sundays may look different from Mondays and 1 P.M. may look different from 5 P.M. For decisionmakers that are attempting to understand the impact of statewide programs, computing data to this level of granularity is not practical. The goal of this section is to provide these decisionmakers with summary statistics of CHP system reactive power potential and a comparison to capacitor bank benchmarks in New York. To quantify CHP system reactive power potential, this study analyzes datasets for 29 CHP systems located at different facilities across New York to extract generalized characteristics that will allow these decisionmakers to get a sense of magnitude and reliability of sourcing reactive power from CHP systems. The sections below will characterize the input data, discuss the method for characterizing reactive power supply, provide the results of the analysis, and compare the results to the capacitor bank benchmarks.

3.1 Dataset Characteristics

Data for this analysis was sourced from the NYSERDA DER Integrated Data System [21]. The NYSERDA DER Integrated Data System includes data sets that provide facility, system, and technology characteristic information for DERs across New York. The NYSERDA DER Integrated Data System also contains hourly power output data for the DERs in its database. This study used both the characteristic information and power output data for CHP systems with synchronous generators. In total, 29 CHP systems fit this criterion. Table 3-1 provides a summary of the categorical characteristics of the CHP systems included in the study and Figure 3-1 provides a map with the general locations of the CHP systems contained within this study. Additional characteristic data on the individual CHP system level is provided in Appendix 1.

Table 3-1. Characteristics of CHP systems included in study

Building Type	Residential = 11 Health Care (Inpatient) = 5 Education = 2 Lodging = 2 Office = 2 Agricultural = 1 Food Sales = 1 Utilities Water and Waste Management = 1 Manufacturing = 1 Public Order and Safety = 1 Public Assembly = 1 Warehouse and Storage = 1	
NYISO Zone	J - New York City = 16 A – West = 3 I - Dunwoodie = 3 C - Central = 2 F - Capital = 2 E - Mohawk Valley = 1 H - Millwood = 1 K - Long Island = 1	
CHP Prime Mover	Reciprocating Engine = 22 Microturbine = 4 Gas Turbine = 3	
CHP Total Power Rating	0 – 1 MW = 21 1 – 2 MW = 3 2 – 3 MW = 2 4 – 5 MW = 3	

Years of CHP Operational Data	Mean = 4.4 Median = 4.0	

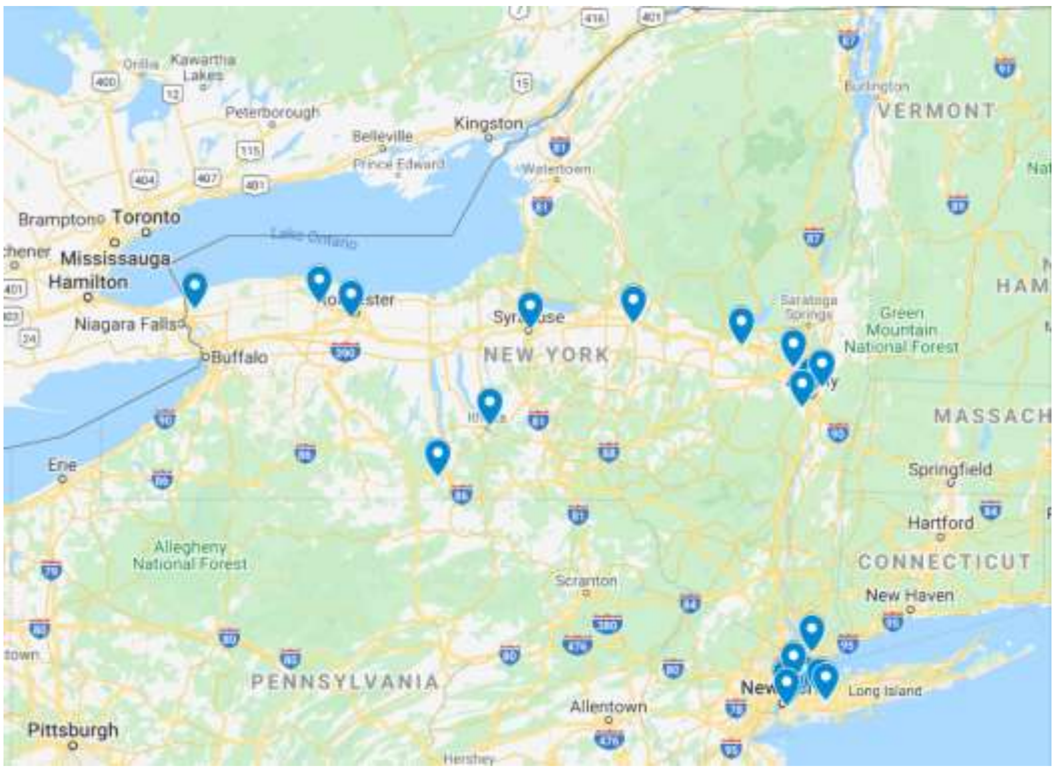


Figure 3-1. Map of CHP systems included in study

3.2 Data Preparation

Due to imperfect data capture and a lack of certain site and technology characteristic information, a number of assumptions were made to analyze the data. First, this study assumed that voltage remained constant at the rated voltage of the generator. Second, it assumed that, for any given site, the CHP system real power output rating ($P_{max,CHP}$) was the installed electric generation capacity identified in the NYSERDA database [21]. Additionally, duplicates in timestamps due to daylight savings time adjustments were removed to prevent errors in the algorithm. In all instances, the first entry for the timestamp was kept. Finally, assumptions for the relationship between $P_{max,CHP}$ and maximum apparent power output ($S_{max,CHP}$) were also necessary to calculate the maximum lagging reactive power ($Q_{max,CHP}$), conventionally shown as positive VARs, and the maximum leading reactive power ($Q_{min,CHP}$), conventionally shown as negative VARs. $P_{max,CHP}$ was assumed to be 0.85 pu with $S_{max,CHP}$ as the base unit. $S_{max,CHP}$ was therefore calculated as $\frac{P_{max,CHP}}{0.85}$. The $Q_{max,CHP}$ and $Q_{min,CHP}$ values used this $S_{max,CHP}$ as the base to convert units from pu to VARs.

3.3 Method for Evaluating Reactive Power Potential

In the sections below, the study will discuss the techniques used to characterize reactive power supply from CHP systems. First, the study outlines the process for calculating reactive power capacity and then addresses characterization at the individual site and New York state levels.

3.3.1 Calculation of Reactive Power Capacity

Calculation of reactive power for this study was based on the trapezoid-type generic capability curve estimation procedure for synchronous generator outlined by Valverde and Orozco [22]. A capability curve defines the generator's permissible operating region bounded by the equipment's limitations, which are typically: field current, armature current, under-excitation, and mechanical power limits [22], [23]. The field current limit refers to the allowable field winding heating, expressed in terms of a maximum field current. The armature current limit is defined by the allowable armature winding heating, expressed in terms of a maximum armature current. Under-excitation limit occurs at the point where reactive power absorption leads to the loss of synchronism and stator core end heating. Finally, mechanical power limit is the maximum mechanical output that can be extracted from the prime mover.

Because CHP system power factor limits were not provided, this study uses linear approximations of the generic generator capability curve outlined by Vlaverde and Orozco to estimate realistic leading and lagging reactive power limits that take field current, armature current, under-excitation, and mechanical power limits into account. To normalize the curves, both active and reactive power are shown in pu, with the CHP system's apparent power rating as the base unit. In Figure 3-2, lagging reactive power, or an over-excited condition, is plotted as a positive pu. Leading reactive power, or an under-excited condition, is plotted as a negative pu.

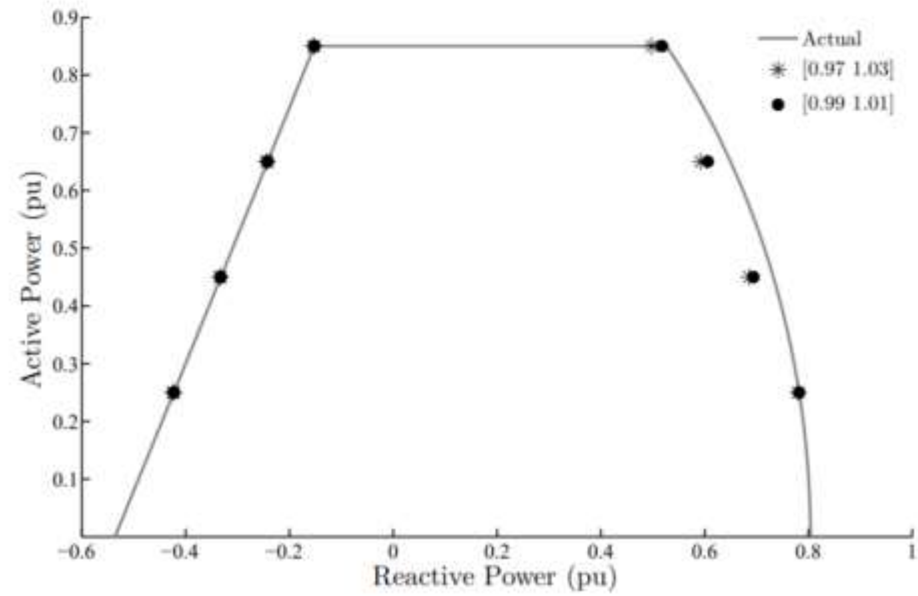


Figure 3-2. Trapezoid-type generic and actual synchronous generator capability curves for V = 1 pu [22]

Table 3-2. Synchronous machine parameters [22]

S_{nom}	3.25 MVA	X_l	0.124 pu	m	0.10 pu
V_{nom}	4.16 kV	X_d	2.013 pu	n	6.03 pu
I_a^{max}	1.00 pu	X_q	1.980 pu	I_f^{max}	2.81 pu

The generic synchronous generator curve can be approximated by taking Q_{max} and Q_{min} at P_{max} and P_{min} and extrapolating a line equation between those points. Per the curve estimates generated by Valverde and Orozco, P_{max} is set at 0.85 pu, with Q_{max} at 0.5169 pu and Q_{min} at -0.15241 pu. P_{min} is 0 pu with Q_{max} at 0.8919 pu and Q_{min} at -0.53533 pu. Zero real power output or missing data were both interpreted as outage events. Whether planned or unplanned, the absence of real power output or the inability of the meter to measure real power output both were assumed to result in an inability to provide reactive power service to the distribution network. Therefore, zero real power output or missing data were interpreted as zero Q_{max} and Q_{min}. The resulting equations used to estimate Q_{max} and Q_{min} are shown in Table 3-3.

Table 3-3. Equations for estimating generic synchronous generator capability curve

$\frac{P_h}{S_{max}}$	Q_{max}	Q_{min}
$0 < \frac{P_h}{S_{max}} \leq 0.85$	$-0.44\ P_h + 0.8919$	$0.4505\ P_h - 0.53533$
0 or Missing Data	0	0

Finally, it should be noted that, while behind-the-meter consumption or absorption of reactive power is an option in realistic conditions, the information required to quantify this activity was not available for the sites used in this study. Therefore, the reactive power potential identified below includes leading and lagging reactive power available both for self-consumption and for the distribution system.

3.3.2 Characterization at the Individual Site Level

Characterization at the individual site level focused on understanding the technical ability to source reactive power from CHP systems at a given location. Given the criticality of reactive power to voltage stability, and therefore grid reliability, the fidelity between predicted production of reactive power and actual production is important. In addition to being predictable, CHP systems should also demonstrate high availability as another factor of reliability. Before utilities will consider procurement of reactive power from CHP systems, there must be evidence that they can do so predictably. To this end, the sections below outline methods for quantifying CHP system reactive power capacity predictability and reliability.

3.3.2.1 SARIMAX Prediction

This study provides a sense of predictability by developing a Seasonal Autoregressive Integrated Moving Average with eXogenous regressors (SARIMAX) model. The Autoregressive Integrated Moving Average (ARIMA) family of prediction models, codified by Box and Jenkins, have been cited often in the literature as a reliable model for time series forecasting [24], [25]. ARIMA models use autoregression (AR), moving average (MA), and differencing (I) terms for their predictions. The AR component looks at a user-defined number of lagged observation values to make its next prediction. The variable ψ is used to designate the number of observations used to define AR. The MA component looks at the residual error between a user-defined number of lagged observation values and a moving average to make its next prediction. The variable ξ is used to designate the number of observations used to define MA. The I term subtracts the previous observation from the current observation to make the time series stationary – in other words, it removes systemic upward or downward trends in the data. A time series is stationary when the mean and variance are constant over time. The variable d is used to designate the number of times the series is differenced.

SARIMA models modify the ARIMA prediction by adding a seasonal component. The variables Ψ, Ξ, and D are used to designate the number of observations for the seasonal autoregressive order, seasonal moving average order, and seasonal difference order respectively. It also has a fourth variable, m, that designates the number of time steps, in this case hours, between seasons.

SARIMAX models add further modifications to the model by incorporating exogenous terms into the regression. In this model, Fourier terms, or terms representing sine and cosine functions, are added as exogeneous terms to incorporate weekly and yearly cycles into the model [26]. The SARIMAX model can be described by the following equation [27]:

$$\Theta(L)^{\psi}\theta(L^m)^{\Psi}\Delta^d\Delta_m^D y_t = \Phi(L)^{\xi}\phi(L^m)^{\Xi}\Delta^d\Delta_m^D \varepsilon_t + \sum_{i=1}^{n}\beta_i x_t^i$$

Where:

ψ = number of time lags to regress on for AR term
ξ = number of time lags to regress on for MA term
d = order of differencing used
Ψ = number of time lags to regress on for seasonal AR term
Ξ = number of time lags to regress on for seasonal MA term
D = order of seasonal differencing used
m = number of time lags comprising one full period of seasonality
t = time
L = lag operator
y_t = time series
$\Theta(L)^p$ = an order p polynomial function of L
$\theta(L^m)^P$ = an order P polynomial function of seasonal L^m
Δ^d = integration operator where $y_t^{[d]} = \Delta^d y_t = y_t^{[d-1]} - y_{t-1}^{[d-1]}$
Δ_m^D = integration operator for seasonal differences
$\Phi(L)^q$ = an order q polynomial function of L
$\phi(L^m)^Q$ = an order Q polynomial function of seasonal L^m
ε_t = noise at time t
n = maximum number of exogenous variables
i = number of exogenous variable
x_t^i = exogenous variables for $i \leq n$ at time t
β_i = coefficient estimated by model for exogenous variables for $i \leq n$

Finally, the prediction model excludes any day whose output is less than 24 kWh. This limit is set to provide some allowance for the model to include instances in which the CHP system is purposefully shut down on a daily basis as part of the operational schedule, but exclude extended outages that don't reflect normal operation.

SARIMAX models require the user to input seven parameters – three parameters to define the ARIMA model (ψ, d, ξ) and four parameters to define the added seasonal component

(Ψ, D, Ξ, m). There is also the option to add exogenous variables to add additional cyclic trends to the prediction. This model also requires user input of Fourier terms (x) as necessary to characterize weekly and yearly cycles, as summarized in Table 3-4.

Table 3-4. Fourier terms considered in SARIMAX model

	Variable	SARIMAX Exog Code
Weekly Cycles	x^1	np.sin(2 * np.pi * exog.index.dayofyear / 168)
	x^2	np.cos(2 * np.pi * exog.index.dayofyear / 168)
	x^3	np.sin(4 * np.pi * exog.index.dayofyear / 168)
	x^4	np.cos(4 * np.pi * exog.index.dayofyear / 168)
Annual Cycles	x^5	np.sin(2 * np.pi * exog.index.dayofyear / 8760)
	x^6	np.cos(2 * np.pi * exog.index.dayofyear / 8760)
	x^7	np.sin(4 * np.pi * exog.index.dayofyear / 8760)
	x^8	np.cos(4 * np.pi * exog.index.dayofyear / 8760)

Each dataset was split into a training set, which consisted of the first 75% of data rows, and a test set, which consisted of the remaining 25% of data rows. The training set was used for model parameter selection and the test set was used to evaluate the performance of the model. Walk-forward cross-validation with four splits was performed on three sites, selected at random. The resulting average root mean square error (RMSE) and mean absolute error (MAE) were compared to the RMSE and MAE from the full training set [28]. The average RMSE and MAE for the four splits either matched or were within 0.03 of the corresponding values from the full training set, so selection of parameters proceeded using RMSE and MAE from the full training set in order to minimize computational power requirements.

Parameter selection was an iterative process. To start, this study selected a baseline set of parameters for a SARIMAX model which was run for all 29 sites. In order to select the three baseline parameters of the ARIMA component, this study first used diagnostic plots available through the seasonal_decompose feature in the python statsmodel module [29]. Examples of these plots are shown later on in the discussion of results in Figure 3-3. The Observed plot provides a view of the actual reactive power output. This sheds light on potential seasonality within the data and glaring issues that might impact the model results, like large gaps or irregular drops and spikes. The Observed plots demonstrated the presence of daily trends, so a frequency of 24 hours was selected.

The Trend plot shows systematic increases or decreases in the data once the user-inputted frequency is excluded. If systemic upward or downward trends remain, this would indicate the dataset might need to be differenced. In other words, this would suggest a d parameter of 1 should be considered. The Trend plot also provided indications on Fourier terms that might need to be included as exogenous regressors. Cycles on the weekly and yearly timescale determined whether their respective regressors were included during the parameter evaluation process. Across the 29 sites, systematic trends were not uniformly observed. Consequently, a d parameter of 0 and no Fourier terms were included as parameters in the baseline model.

The Seasonal plot helps confirm the timesteps of a potential cyclic trend. All 29 sites exhibited seasonality on a daily cycle, so a timestep, or m, of 24 was used in all cases and D was set to 1. Finally, the Residual plot shows the random noise of the data set. This was not used to select parameters.

Once seasonal_decompose provided guidance on d, m, D and the Fourier terms, the study then tested the remaining parameters $\psi, \xi, \Psi,$ and Ξ for significance by running the SARIMA model with (ψ, d, ξ), (Ψ, D, Ξ, m) parameters of (1,0,1), (1,1,1,24) without Fourier terms. To minimize computational power requirements for these calculations, $\psi, \xi, \Psi,$ and Ξ were only assessed at a lag value of 1. Using the Statespace Model Results, all parameters were evaluated for p-values less than 0.05. P-values greater than 0.05, RMSE, and MAE were noted. Of the 29 sites, 7 sites had 1 parameter that had a p-value greater than 0.05. The remaining 22 sites showed p-values less than or equal to 0.05. Therefore, a baseline SARIMA model with parameters of (1,0,1), (1,1,1,24) was chosen.

From the baseline model, the study further assessed model improvements by 1) excluding model parameters that demonstrated p-values greater than 0.05 and 2) adding in Fourier terms. The 7 sites with parameters with p-value greater than 0.05 were rerun with those parameters set to 0. Then, seasonal_decompose trend plots were evaluated for weekly or annual patterns. If a pattern appeared to exist, the respective Fourier terms were included and the model was rerun. If a p-value was greater than 0.05 for any Fourier term, the term was excluded from the model and the model was rerun. Once all selected terms demonstrated significance, the RMSE and MAE were calculated and noted. These SARIMAX model RMSE and MAE were compared to the baseline

SARIMA model RMSE and MAE. The model with the smaller RMSE was selected as the model that would be used for the remainder of the study.

3.3.2.2 Calculation of Availability

Availability is a percentage representing the proportion of hours a power generation unit is able to produce power to the total number of hours within that time period [30]. To estimate availability for reactive power, this study calculated the proportion of hours with non-zero CHP system real power output to total hours included in each site's data set. Under the assumption that CHP systems would not change their real power production patterns to provide reactive power, this approach should provide a credible value for availability since reactive power would only be produced when the CHP system was producing real power. If this assumption is lifted, the availability estimates should be expected to be higher than is reported in this study. To prevent the impact of start-up and commissioning of the CHP system or meter from skewing the data, the first 600 hours have been excluded. The calculation of availability can be represented by the following equation:

$$a_{b,CHP} = \frac{z_{b,CHP}}{t_{b,CHP}} * 100\%$$

Where:

b = site
$a_{b,CHP}$ = CHP system availability for a given site
$z_{b,CHP}$ = total number of hours where zero power was produced for a given site
$t_{b,CHP}$ = total hours included in a dataset

3.3.3 Characterization at the New York State Level

The goal of characterizing the reactive power potential from CHP systems is to provide a sense of the magnitude, variance, and availability of the reactive power that could be produced or absorbed if a market existed to support these transactions. In order to understand the potential at the state level, summary statistics characterizing reactive power capacity and prediction error were calculated for the 29 sites. These summary statistics include minimum, average, maximum, and standard deviation for reactive power capacity, root mean square error, and mean absolute error. Summary statistics for minimum, average, maximum, and standard deviation were also calculated for reactive power availability.

3.4 Reactive Power Potential Results

The sections below outline the results of the SARIMAX predictions and availability at the individual site level as well as the summary statistics calculated at the state level.

3.4.1 Reactive Power Potential Results at the Individual Site Level

In order to understand the results for the reactive power potential of CHP systems, this study first looked at results from the individual site level. Table 3-5 provides a summary of the results and data set characteristics used in the individual site level analysis. The RMSE and MAE values for both lagging and leading reactive power are then summed, sorted in ascending order, and color coded in a gradient from green to red to provide an indication of sites whose model predictions performed the best and worst. Green designates the smallest total RMSE and MAE, or sites with SARIMAX predictions that matched actual values well. Red designates the largest total RMSE and MAE, or sites with SARIMAX predictions that had large discrepancies with actual values. In order to understand drivers behind these variances, this study took a deep dive look at the three best (sites c, m, and w) and the worst (sites a, n, and y) performing sites. Individual site mean predictions, RMSE, and MAE for the baseline SARIMA model can be found in Appendix 2. Individual site final parameters, mean predictions, RMSE, and MAE for the SARIMAX model can be found in Appendix 3 and 4. Total overall hours and total hours of zero production per data set underlying availability calculations are available in Appendix 5.

Table 3-5. Total SARIMAX prediction RMSE and MAE, apparent power rating, years of data, and availability per site

Site	Sum of RMSE and MAE (pu)	Apparent Power Rating (kVA)	Years of Data (years)	Availability (%)
m	0.12	1,000	3.8	100%
w	0.16	76	3.6	97%
c	0.19	2,122	3.2	99%
v	0.19	76	6.3	98%
g	0.20	706	8.1	88%
l	0.21	6,588	8.8	96%
h	0.23	5,412	5.0	94%
j	0.24	918	6.2	99%
e	0.25	5,294	3.4	94%
f	0.25	294	7.4	95%
u	0.25	235	2.8	91%
z	0.28	935	0.4	96%
i	0.30	659	1.1	83%
d	0.31	165	4.0	72%
r	0.31	353	4.7	97%
aa	0.32	118	2.9	75%
b	0.33	2,328	3.2	97%
q	0.35	76	6.9	96%
s	0.35	176	4.0	90%
x	0.35	176	3.9	73%
o	0.38	2,418	4.2	41%
p	0.42	88	4.0	99%
cc	0.43	2,941	6.7	40%
k	0.44	312	1.1	79%
t	0.47	88	2.9	70%
bb	0.52	235	2.9	93%
y	0.54	88	4.3	92%
a	0.59	153	3.9	62%
n	0.61	1,882	8.3	21%

3.4.1.1 Comparison of Sites c, m, and w to Sites a, n, and y

To explore potential explanations for the differences in performance for sites c, m, and w and sites a, n, and y, this study looked at both characteristics of each site and observations from the sites' data sets. A review of characteristic data like location (through both zip code and NYISO zone), facility type, and prime mover type showed no obvious potential drivers for the differences in performance. Apparent power rating was also considered. Table 3-5 summarizes this evaluation, with higher apparent power ratings color coded in green and lower apparent power ratings color coded in red. Looking specifically at sites c, m, and w and sites a, n, and y, there does not appear to be a discernable trend associated with apparent power ratings since both site groupings have CHP systems with high and low ratings. Finally, the years of data contained in each data set was evaluated. Sites c, m, and w all cluster closely to their average of 3.5 years while sites a, n, and y range from 3.9 to 8.3 around their average of 5.5 years. As a result, there does not appear to be a cohesive explanation of model performance based on years of data.

A review of the reactive power seasonal_decompose plots in Figure 3-3 and real power load curves in Figure 3-4 reveal possible drivers for these model performance differences. First, the Observed plots of sites a, n, and y show more frequent and larger gaps in the data. Though days with less than 24 kWh production are excluded from the data set to increase model prediction accuracy, the presence of outages could still have an impact because of the misalignment of days. If, for example, a CHP system had an outage on Tuesday, the data from Tuesday would be excluded and the algorithm would use data from Monday to make its prediction for Wednesday. Increasingly prevalent outages can then be expected to result in higher error rates. This assessment is further underlined by the general pattern clustering of high availabilities observed for sites m, w, and c and low availabilities for a and n. Site y does actually demonstrate a relatively high availability, suggesting that other factors might have contributed more significantly to its error rates as discussed below.

Second, the Residual plots for sites c, m, and w show a relatively tight distribution around 0, whereas sites a, n, and y show larger variances. This suggests that most of the fluctuation in kVAR output for sites c, m, and w can be explained by daily seasonality. This assertion is further underlined upon examination of the daily real power load profiles. Sites c, m, and w have relatively well-defined daily patterns, which translates to a consistent ability to output consistent amounts of lagging and leading reactive power. The exception to this assessment is site n, which does appear to also have a defined daily pattern. This suggests that outages might have played a bigger role in RMSE and MAE for that site. Site that are best predicted by SARIMAX algorithms, then, are those that have well-defined and consistent daily patterns.

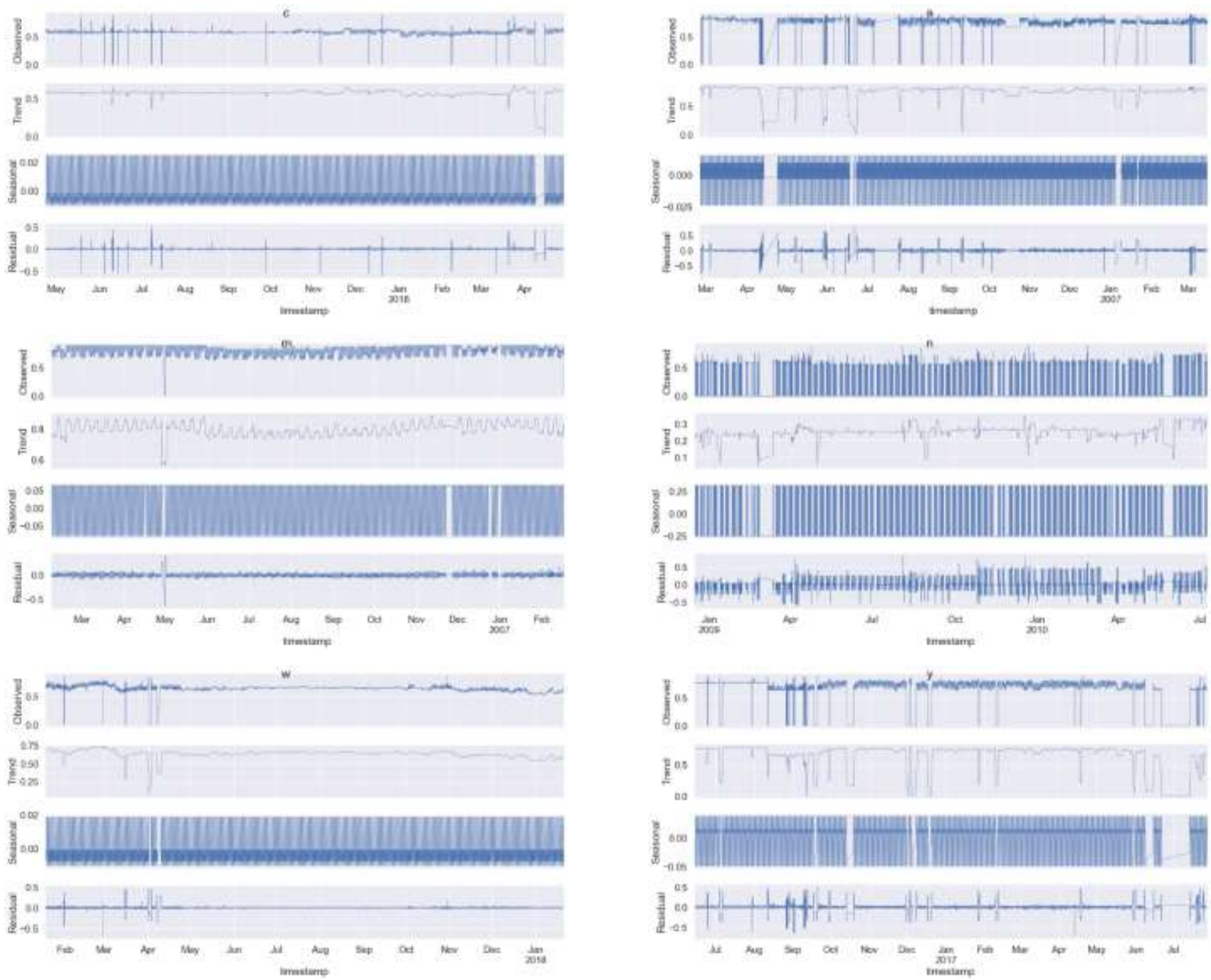


Figure 3-3. Seasonal_decompose plots from statsmodel Python module for lagging reactive power

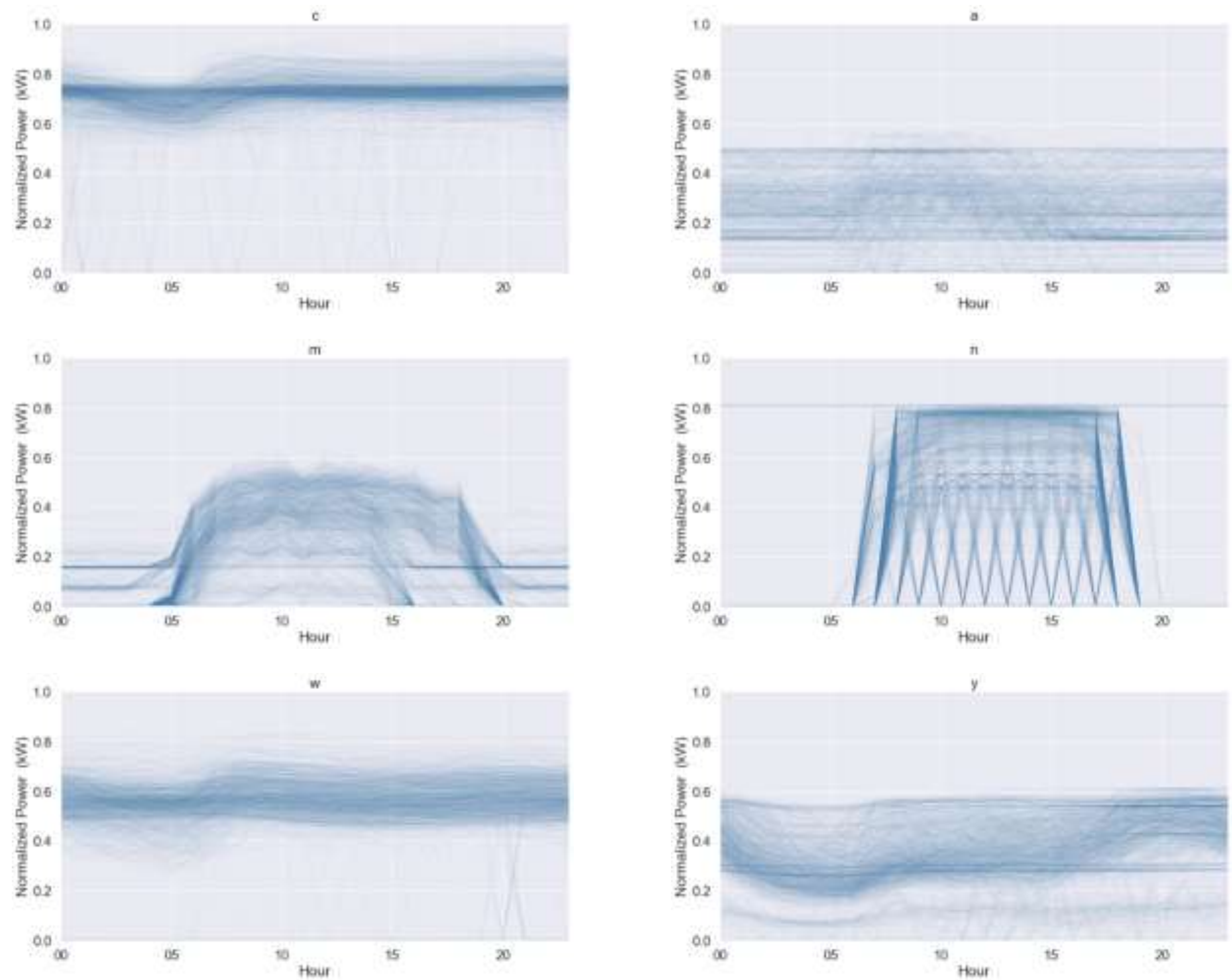


Figure 3-4. Daily normalized real power load curves

3.4.2 Reactive Power Potential Results at the New York State Level

The technical potential of reactive power at the New York state level is promising, but highly variable. Summing the average reactive power capacity across the 29 sites, there was roughly 19.5 MVAR lagging and -8.1 MVAR leading available at any given point in time. The reactive power potential did range widely from site to site. For lagging reactive power, the minimum site average in the data set was 49 kVAR and the maximum was 3,558 kVAR. For leading reactive power, the values ranged from -21 to -1,407 kVAR. When considered on a pu scale, the lagging reactive power range was 0.21 to 0.86 p.u and leading reactive power range was -0.10 to -0.51 pu Given that reactive power was tied to the operational patterns of the CHP system's real power production, this wide range indicated that there are notable differences in the operational patterns of the systems among sites. These operational differences were visually confirmed by the plots of daily lagging and leading reactive power potential in Appendix 6 and 7.

The RMSE values also indicated uncertainty around the predicted values. For any given prediction in a given hour for a given site, on average there was a 68% chance the true lagging reactive power potential value was actually +/- 157 kVAR and 0.14 pu from that prediction. To increase the probability to 95%, the window increased to +/- 314 kVAR and 0.28 pu. For leading reactive power, the window for 68% likelihood of capturing the true value was +/- 84 kVAR and 0.08 p.u and for 95% was +/- 168 kVAR and 0.16 pu Given the mean prediction of 674 kVAR and 0.61 pu, that level of uncertainty meant the true value had a high likelihood of being close to 0.5 or 1.5 times the predicted value.

MAE values further reinforced this uncertainty. The average lagging reactive power was 69 kVAR and 0.07 pu across all 29 sites, but had individual sites that showed MAE values as low as 2 kVAR and 0.02 p.u and as high as 301 kVAR and 0.16 pu. The average leading reactive power was 48 kVAR and 0.05 pu, but ranged from 2 kVAR and 0.02 pu to 212 kVAR and 0.09 pu Again, against a mean prediction of 675 kVAR and 0.61 pu, this represents a high overall error.

From an availability standpoint, the average value of 84% uptime and standard deviation of 20% adds further uncertainty. It should be clarified that this uptime value does not distinguish between zero reactive power production due to unintended system outages and zero production due to intentional scheduling in the operational plan. Both result in the inability to produce reactive power under the assumption in this study that CHP systems wouldn't change their operational plans to produce reactive power.

Altogether, the estimated reactive power potential for a synchronous generator CHP system in New York is, on average, 674 kVAR and 0.61 pu lagging and -281 kVAR and -0.28 pu leading. However, there are high levels of uncertainty around these numbers, driven by differences in CHP rated capacity, operational characteristics, predictability of operational patterns, and system availability.

Table 3-6. Reactive power potential across New York State

Summary Statistic	Lagging Reactive Power (pu)			Leading Reactive Power (pu)			Lagging Reactive Power (kVAR)			Leading Reactive Power (kVAR)		
	Mean Prediction	RMSE	MAE	Mean Prediction	RMSE	MAE	Mean Prediction	RMSE	MAE	Mean Prediction	RMSE	MAE
Min	0.21	0.04	0.02	-0.51	0.04	0.02	49	5	2	-1,407	3	2
Average	0.61	0.14	0.07	-0.28	0.08	0.05	674	157	69	-281	84	48
Max	0.86	0.26	0.16	-0.10	0.14	0.09	3,558	595	301	-21	353	212
St. Dev	0.13	0.05	0.03	0.09	0.03	0.02	979	214	93	378	110	62

Table 3-7. Availability of CHP system reactive power across New York State

Summary Statistic	Total # Hours	# Hours >0 kWh	# Hours 0 kWh	Availability
Min	3,720	3,558	121	21%
Average	38,033	31,092	6,941	84%
Max	77,208	73,819	57,725	100%
St. Dev	18,179	16,902	12,296	20%

3.5 Characterization of Capacitor Bank Reactive Power Potential

Capacitor banks can be sized to fit the specific needs of a feeder. This study assumes that capacitor banks can be sized to match any CHP system reactive power capacity identified in the data set. For the purposes of this study, the capacitor banks were assumed to be fixed. Consequently, the capacitor bank only has two modes: "on," in which the capacitor bank is producing leading reactive power, and "off," in which the capacitor bank is not producing any reactive power. This characteristic also makes the capacitor bank's behavior fairly predictable, since the capacity and output when "on" is at the rated capacity of the capacitor bank. However, this characteristic does create some inefficiency in the distribution network since the power factor cannot be granularly changed to move it closer to 1 and minimize real power losses.

Estimates in the literature on availability and failure rates for capacitor banks are not commonly cited. A 2008 paper by Zhu uses a 1% annual failure rate for capacitor banks [31]. An ABB presentation from 2017 lists a 0.1% failure rate for their capacitor banks [32]. Finally, a 2018 paper by Velásquez reported an annual expected availability of 99.87% [33]. This study will assume a 1% annual failure rate and therefore a 99% availability.

3.6 Comparison of CHP System and Capacitor Bank Reactive Power Potential

CHP system reactive power potential appears to be unfavorable to capacitor banks from both a predictability and availability standpoint. Under the assumptions of this study, CHP systems showed a wide range of predicted lagging and leading reactive power output capacity, driven by the strength of daily real power output patterns and availability of the system. CHP systems have the potential to control the nature and magnitude of the lagging or leading reactive power it produces up to these limits, which is desirable from a utility perspective. Capacitor banks, on the other hand, are sized at a rated capacity and can either be turned on or off. In other words, capacitor banks are either on and producing their fully rated capacity, or are off and not producing any reactive power. This characteristic makes them highly predictable and easy to model.

Furthermore, CHP systems show a wide range of availabilities. Though the average of 84% availability is not bad, the variance around this average is significant. When compared to the reported 99% availabilities of capacitor banks, CHP system availability does not show favorably.

The case is not strong for CHP systems to completely displace the technical ability of capacitor banks to provide a reliable source of reactive power. However, with 19.5 MVAR lagging and -8.1 MVAR leading reactive power capacity available in the New York system network, CHP systems could be considered to supply reactive power as a complement to capacitor bank supply.

Chapter 4 – Cost Estimation of Reactive Power

Now that the technical opportunity for procuring reactive power from CHP systems has been characterized, the second part of assessing its value is understanding the potential cost. It is also important to understand the cost of the conventional solution to get a sense of the economic viability of sourcing reactive power from CHP systems. Assuming the technical capabilities of reactive power from CHP systems are acceptable, utilities would then need to compare costs with existing solutions to ensure they are upholding their responsibility to deliver power cost-effectively. In the sections below, methods for estimating the potential cost of procuring reactive power from CHP systems and conventional sources are suggested and the resulting estimated costs provided.

4.1 Method for Estimating Reactive Power Cost for CHP Systems

To estimate the cost of sourcing reactive power from CHP systems, this study took two approaches. First, the study looked at the annual compensation rate provided to generators that produced reactive power at the transmission level. Second, it took a bottom up approach and estimated cost based on assumptions on the operation of CHP systems.

4.1.1 Reactive Power Cost Approximation using NYISO Compensation Rate

An approximation of the cost of reactive power can be assessed by looking at the current compensation rate of reactive power procurement at the transmission level, as determined by the NYISO. In the NYISO Market Administration and Control Area Services Tariff, published on 7/11/2019, Voltage Support Service is set to be compensated at $2,592 / MVAR annually for both leading and lagging reactive power, based on capacity [34]. Including the adjustment for the Consumer Price Index, the annual rate for January 2020 would be $2,858.55 / MVAR or $2.86 / kVAR [35]. Assuming 2/3 of this capacity is used on average across the year, this is the equivalent of $0.00049 / kVARh. The additional lost opportunity cost calculated for NYISO suppliers is not applicable for CHP systems because the assumption used in this study is that reactive power will only be produced in excess of the CHP system's real power needs. Therefore, CHP systems will not have to make a trade-off with real power production.

4.1.2 Reactive Power Cost Approximation using CHP System Data

Alternatively, cost can be approximated using a bottom up approach by estimating operational costs incurred by CHP systems as they produce reactive power. Initial capital and installation expenses were not included in this estimate because this study assumed CHP systems would have already been installed – therefore, the expected revenue from reactive power would not have been accounted for in the purchasing process. The inputs for these calculations were primarily based on characteristic and operational data from the 29 sites included in this study. Where information was not available or not sufficiently provided for all 29 sites, assumptions were made based on information found in the literature. These costs were purely based on operational assumptions which do not account for program administration and one time set up costs.

The components of operational cost that were factored into this study were fuel cost, electrical efficiency, impact of reactive power output on electrical efficiency, real power output, reactive power output, and reactive power capacity. Given the variability of each of these components, this study looked at three scenarios. Scenario 1 looked at assumptions that would result in low operational cost, scenario 2 at average operational cost (or midpoints if averages aren't available), and scenario 3 at maximum operational cost. The final assumptions used in the cost assessment are outlined in Appendix 8 and 9.

Fuel cost was based on National Grid's Total Effective Monthly Cost of Gas (per therm) for SC12 Distributed Generation [36]. Given the volatility of gas prices month to month, this study used a three year minimum, average, and maximum from January 2015 to December 2018. All values were adjusted for inflation based on the U.S. Consumer Price Index inflation calculator for January 2020. The resulting cost was $0.12 / therm for scenario 1, $0.28 / therm for scenario 2, and $0.55 / therm for scenario 3. Fuel cost was converted to $/therm to $/kWh using the energy conversion ratio of 1 therm = 29.3001 kWh.

Not all fuel converts to electricity in the power generation process, so a value for CHP system electrical efficiency had to be assumed. Given that many of the 29 sites did not report this value, this study turned to a CHP system evaluation protocol published by NREL in 2016 and CHP fact sheet published by the U.S. Department of Energy in 2017 [18], [37]. 22 of the 29 CHP sites had reciprocating engines, so this study used efficiencies listed in the two studies for reciprocating or internal combustion engines. The NREL report listed a range of 27%-41% higher heating value (HHV) while the U.S. Department of Energy listed a range of 30-42% (HHV). The electrical efficiencies chosen for this study were 42% for scenario 1, the midpoint of 34.5% for scenario 2, and 27% for scenario 3.

Next, an assumption was made for the impact reactive power production had on electrical efficiency. In a 2008 study conducted by Oak Ridge National Lab on developing a tariff for reactive power, the authors assumed that losses due to reactive current flow were 2% [11]. Another 2008 study by Braun estimated losses to be between 1 – 5%, with losses increasing as apparent power production increased to its rated capacity [38]. Assuming reactive power would typically not force the CHP system to push power production to its full rating, this study used a 2% efficiency loss in its calculation. Finally, real power output, reactive power output, and reactive power capacity were determined using operational data from the 29 sites in the dataset. To maintain consistency with the assumption used in the NYISO approximation, this calculation also assumed that 2/3 of reactive power capacity was discharged over the year.

The formulas for determining the equivalent annual costs for each scenario based on both capacity and total kVARh production were as follows:

$$EAC_{Q,CHP,kVAR} = \frac{\sum_{b=1}^{B} \frac{e_{b,CHP} * \frac{2}{3} * f}{Q_{b,cap}}}{B}$$

$$EAC_{Q,CHP,kVARh} = \frac{\sum_{b=1}^{B} \frac{e_{b,CHP} * f}{Q_b}}{B}$$

Where:

$EAC_{Q,CHP,kVAR}$ = equivalent annual cost of reactive power from CHP system based on capacity
$EAC_{Q,CHP,kVARh}$ = equivalent annual cost of reactive power from CHP system based on total reactive power produced
b = site
B = total number of sites
$e_{b,CHP}$ = total energy produced for a given site
f = fuel cost
$Q_{b,cap}$ = reactive power capacity for a given site
Q_b = total reactive power produced in a year for a given site

4.2 Method for Estimating Reactive Power Cost for Capacitor Banks

In order to compare the life-cycle cost of reactive power sourced from capacitor banks to that of CHP systems, the equivalent annual cost ($E_{Q,CB}$) was calculated. The calculation assumed the capacitor bank's life-span was 15 years and the cost of capital was 6.85% [9], [39].

$$EAC_{Q,CB,kVAR} = \frac{c_{CB} + I_{CB}}{\frac{1-(1+r)^{t_{CB}}}{r}} + M_{CB}$$

$$EAC_{Q,CB,kVARh} = \frac{EAC_{Q,CB,kVAR}}{8{,}760 * \frac{2}{3}}$$

Where:

$EAC_{Q,CB,kVAR}$ = equivalent annual cost of reactive power from a capacitor bank based on capacity
$EAC_{Q,CB,kVARh}$ = equivalent annual cost of reactive power from a capacitor bank based on total reactive power produced
c_{CB} = capital cost of the capacitor bank
I_{CB} = installation cost of the capacitor bank
M_{CB} = maintenance cost of the capacitor bank
t_{CB} = expected life-span of capacitor bank
r = weighted average cost of capital

These values are based off of costs identified from a variety of sources, which are summarized in Appendix 9. All costs are adjusted for inflation to the purchasing power of the January 2020 dollar based on the U.S. Consumer Price Index inflation calculator [35]. Calculations of the hourly cost of reactive power assume that, on average, the capacitor bank is utilized at 2/3 of its nameplate capacity to match the assumptions used for the CHP system cost analysis [40].

4.3 Reactive Power Cost Estimate Results

Table 4-1 and Table 4-2 summarize the calculated equivalent annual costs for CHP systems and capacitor banks respectively, both by capacity and hourly cost.

Table 4-1. CHP system equivalent annual costs

Cost Scenario	$E_{Q,CHP}$ - Capacity	$E_{Q,CHP}$ – Hourly
NYISO	\$2.86 / kVAR	\$0.00049 / kVARh
Scenario 1	\$0.78 / kVAR	\$0.00026 / kVARh
Scenario 2	\$2.75 / kVAR	\$0.00093 / kVARh
Scenario 3	\$8.93 / kVAR	\$0.00302 / kVARh

Table 4-2. Capacitor bank equivalent annual costs

Cost Scenario	$E_{Q,CB}$ **- Capacity**	$E_{Q,CB}$ **– Hourly**
Scenario 1	\$1.19 / kVAR	\$0.00020 / kVARh
Scenario 2	\$3.47 / kVAR	\$0.00059 / kVARh
Scenario 3	\$7.92 / kVAR	\$0.00136 / kVARh

4.4 Comparison of CHP System and Capacitor Bank Equivalent Annual Costs

Based on the methods outlined above, the comparative results were mixed. Figure 4-1 and Figure 4-2 provide visualizations for the comparative annualized costs for reactive power sourced from CHP systems – based on both NYISO's compensation rate and the bottom up approach using operational data from the 29 sites – and from capacitor banks across the three scenarios. From a capacity standpoint, reactive power cost for CHP systems based on average and midpoint assumptions in scenario 2 appeared to be close to the compensation that was derived from the NYISO compensation rate. The CHP system reactive power costs were \$1.67 / kVAR lower than a capacitor bank based on minimum assumptions in scenario 1 and \$1.01 / kVAR higher based on maximum assumptions in scenario 3. From a total annual reactive power production standpoint, the CHP system operational method suggested a higher cost per kVARh compared to the capacitor bank in all three scenarios. The NYISO cost method reflected the highest cost in scenario 1, but is the lowest for both scenario 2 and 3.

If a fair compensation rate falls somewhere between the NYISO and operational cost methods, there is an argument to be made that sourcing reactive power from CHP systems can be economically competitive with capacitor banks. The economic case for CHP system reactive power becomes stronger as gas prices fall, system efficiency improves, and when reactive power is produced at times when total apparent power is further from rated capacity.

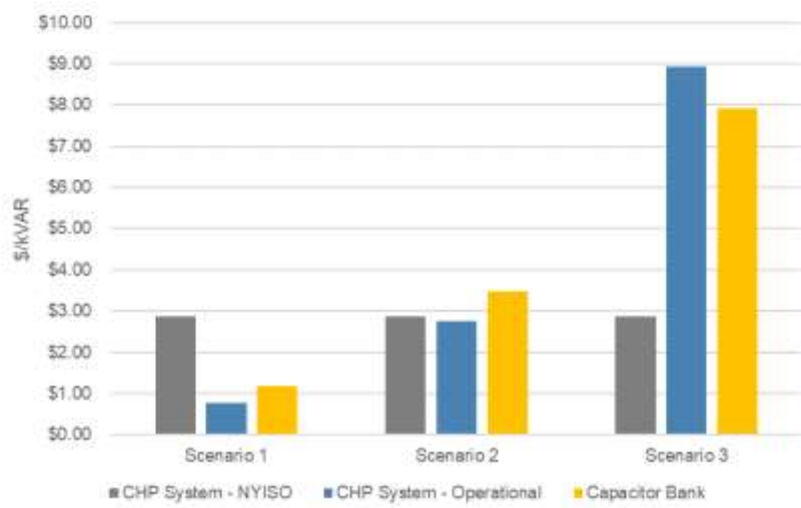


Figure 4-1. CHP system and capacitor bank annual cost comparison based on capacity

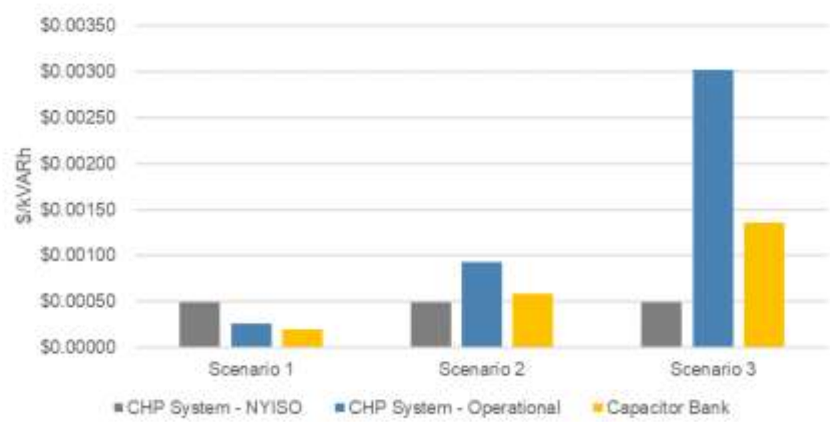


Figure 4-2. CHP system and capacitor bank annual cost comparison based on hourly cost

Chapter 5 – Conclusions and Recommendations

This study provides indications that sourcing reactive power from CHP systems can be competitive with installations of capacitor banks in select scenarios. There is evidence that there is sufficient capacity in the CHP systems to produce reactive power that can be exported to the distribution network. However, the exact amount varies greatly between sites and over time. This uncertainty is further compounded by the inability to reliably predict these varying amounts and the comparably low availability consistently across sites evaluated in this study. To a utility whose foundational responsibility is to provide reliable power for its customers, this level of uncertainty is likely not attractive. Contrasted with the ability to size capacitor banks as needed, the estimated 99% availability, and predictability of behavior characterized by capacitor banks, the technical value proposition is not strong. There are some efficiency benefits to enabling more granular reactive power production and absorption, but increases in efficiency are undoubtedly lower priority than reliability. This suggests there may be potential in sourcing reactive power from CHP systems as a complement to the reactive power sourced from capacitor banks.

From an economic perspective, the analysis shows scenarios in which CHP sourced reactive power does appear to be competitive with capacitor banks. The economic value proposition for CHP systems improves as fuel efficiency improves, gas costs decrease, and when total apparent power remains low during reactive power production. This comparability of cost further suggests the potential viability of sourcing reactive power from CHP systems as a complement to capacitor banks.

Reactive power is an important mechanism for maintaining a reliable grid. As the New York power system interconnects an increasing amount of intermittent power generation technologies and as operational coordination, planning, and market design become increasingly complex, reactive power and need for voltage support can be expected to increase as well. Though the findings in this thesis do suggest a potential role for CHP systems in a DSP framework, further study is required before determining whether they should be incorporated into the framework.

More detailed studies and considerations must be taken before taking operational action. First, this study does not factor in potential operational changes that could be driven by economic incentives and does not capture the ability of individual sites to demonstrate characteristics that can be very well suited for providing reactive power in a predictable and reliable manner. To this end, this study recommends a case-study approach to develop a more in-depth, site specific analysis on the fit between CHP system reactive power production or absorption and the distribution feeder's needs. More specifically, it is important to understand 1) whether CHP reactive power availability matches with the distribution feeder's demands, 2) whether the use of a more specifically tuned predictive algorithm can provide higher certainty for capacity forecasts and 3) whether times of zero power production can be systematically characterized as planned or unplanned.

Second, the economic incentives must be further evaluated in New York. Though the EACs proved to be comparable between CHP systems and capacitor banks, this metric does not give a sense of whether CHP system owners would choose to supply at that price point. Evaluation of the location-specific value of reactive power must be completed and compared to the operational costs provided in this study. This study also recommends additional customer discovery regarding acceptable compensation, using this value-based assessment of reactive power price as a baseline, before this option is pursued.

Finally, this study recommends similar analysis be pursued with other DERs that have the potential to supply or absorb reactive power. Though the value of creating a marketplace around CHP system reactive power may be insufficient, when combined with other potential sources, there may be sufficient value created to move forward.

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Appendix

1. Characteristic Data for Individual Sites

Site Code	# of Devices	CHP System Rating (kW)	Data Start	Data End	Years of Data	Avg. Annual Energy Output (GWh)
a	1	130	6/1/2005	5/1/2009	3.9	0.22
b	1	1979	9/10/2016	11/28/2019	3.2	11.90
c	1	1804	9/1/2016	11/21/2019	3.2	12.95
d	1	140	11/28/2007	11/30/2011	4.0	0.32
e	1	4500	4/1/2013	8/27/2016	3.4	31.15
f	1	250	9/1/2012	1/21/2020	7.4	1.42
g	8	600	5/1/2008	6/1/2016	8.1	3.94
h	1	4600	12/1/2014	11/21/2019	5.0	25.32
i	1	560	9/1/2001	10/1/2002	1.1	2.79
j	12	780	11/1/2013	1/21/2020	6.2	4.18
k	1	265	12/22/2018	1/21/2020	1.1	1.06
l	7	5600	12/31/2004	10/22/2013	8.8	41.52
m	3	850	6/1/2005	3/9/2009	3.8	0.81
n	2	1600	11/1/2006	2/28/2015	8.3	2.12
o	1	2055	9/1/2015	11/21/2019	4.2	3.47
p	1	75	2/1/2016	1/21/2020	4.0	0.34
q	1	65	3/1/2013	1/21/2020	6.9	0.25
r	4	300	5/7/2015	1/21/2020	4.7	1.24
s	2	150	3/1/2013	2/27/2017	4.0	0.73
t	1	75	3/1/2017	1/21/2020	2.9	0.34
u	2	200	4/1/2017	1/8/2020	2.8	0.44
v	1	65	10/1/2013	1/21/2020	6.3	0.30
w	1	65	6/1/2016	1/21/2020	3.6	0.37
x	2	150	3/1/2016	1/21/2020	3.9	0.25
y	1	75	10/15/2015	1/21/2020	4.3	0.23
z	3	795	8/19/2019	1/21/2020	0.4	1.96
aa	1	100	3/1/2017	1/21/2020	2.9	0.31
bb	2	200	3/1/2017	1/21/2020	2.9	0.57
cc	2	2500	8/1/2008	4/1/2015	6.7	3.66

2. Baseline SARIMA Model Mean Prediction, RMSE, and MAE for Lagging and Leading Reactive Power Predictions Per Site by pu and kVAR

Site	Apparent Power Rating (kVA)	Lagging Reactive Power (pu)			Leading Reactive Power (pu)			Lagging Reactive Power (kVAR)			Leading Reactive Power (kVAR)		
		Mean Prediction	RMSE	MAE	Mean Prediction	RMSE	MAE	Mean Prediction	RMSE	MAE	Mean Prediction	RMSE	MAE
a	153	0.74	0.24	0.12	-0.40	0.14	0.09	113	37	18	-61	21	14
b	2,328	0.53	0.15	0.07	-0.20	0.07	0.04	1,234	349	163	-476	163	93
c	2,122	0.56	0.08	0.03	-0.19	0.05	0.03	1,188	170	64	-403	106	64
d	165	0.71	0.13	0.07	-0.38	0.07	0.04	117	21	12	-63	12	7
e	5,294	0.55	0.11	0.05	-0.20	0.05	0.04	2,912	582	265	-1,059	265	212
f	294	0.53	0.12	0.04	-0.17	0.06	0.03	156	35	12	-50	18	9
g	706	0.55	0.10	0.04	-0.20	0.04	0.02	388	71	28	-141	28	14
h	5,412	0.61	0.11	0.04	-0.26	0.05	0.03	3,301	595	216	-1,407	271	162
i	659	0.58	0.13	0.06	-0.22	0.07	0.04	382	86	40	-145	46	26
j	918	0.68	0.10	0.05	-0.33	0.07	0.05	624	92	46	-303	64	46
k	312	0.58	0.15	0.12	-0.26	0.09	0.08	181	47	37	-81	28	25
l	6,588	0.54	0.09	0.04	-0.19	0.05	0.03	3,558	593	264	-1,252	329	198
m	529	0.84	0.06	0.04	-0.48	0.06	0.04	444	32	21	-254	32	21
n	1,882	0.21	0.26	0.16	-0.10	0.12	0.07	395	489	301	-188	226	132
o	2,418	0.35	0.17	0.06	-0.16	0.10	0.05	846	411	145	-387	242	121
p	88	0.62	0.17	0.08	-0.24	0.10	0.07	55	15	7	-21	9	6
q	76	0.72	0.12	0.07	-0.36	0.10	0.06	55	9	5	-27	8	5
r	353	0.65	0.11	0.06	-0.29	0.08	0.06	229	39	21	-102	28	21
s	176	0.62	0.12	0.07	-0.26	0.09	0.07	109	21	12	-46	16	12
t	88	0.59	0.19	0.09	-0.29	0.11	0.08	52	17	8	-26	10	7
u	235	0.63	0.06	0.03	-0.42	0.11	0.05	148	14	7	-99	26	12
v	76	0.62	0.08	0.05	-0.29	0.05	0.04	47	6	4	-22	4	3
w	76	0.62	0.07	0.04	-0.25	0.05	0.04	47	5	3	-19	4	3
x	176	0.73	0.13	0.07	-0.37	0.09	0.06	128	23	12	-65	16	11
y	88	0.69	0.21	0.12	-0.34	0.13	0.08	61	18	11	-30	11	7
z	935	0.73	0.12	0.06	-0.39	0.07	0.03	683	112	56	-365	65	28
aa	118	0.60	0.16	0.05	-0.29	0.08	0.03	71	19	6	-34	9	4
bb	235	0.74	0.21	0.11	-0.38	0.12	0.08	174	49	26	-89	28	19
cc	2,941	0.48	0.20	0.07	-0.24	0.12	0.04	1,412	588	206	-706	353	118

3. Final SARIMAX Model Parameters Per Site

Site	Model Parameters														
	p	d	q	P	D	Q	m	x^1	x^2	x^3	x^4	x^5	x^6	x^7	x^8
a	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
b	1	0	1	1	1	1	24	-	x	-	-	-	-	-	-
c	1	0	1	1	1	1	24	x	-	-	-	-	-	-	-
d	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
e	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
f	1	0	1	0	1	1	24	-	-	-	-	-	-	-	-
g	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
h	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
i	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
j	1	0	1	0	1	1	24	-	-	-	-	x	x	x	x
k	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
l	1	0	0	1	1	1	24	-	-	-	-	-	-	-	-
m	1	0	1	0	1	1	24	-	-	-	-	-	-	-	-
n	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
o	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
p	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
q	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
r	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
s	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
t	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
u	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
v	1	0	1	0	1	1	24	-	-	-	-	-	-	-	-
w	1	0	1	0	1	1	24	-	-	-	-	-	x	-	x
x	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
y	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
z	1	0	1	0	1	1	24	-	-	-	-	-	-	-	-
aa	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
bb	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-
cc	1	0	1	1	1	1	24	-	-	-	-	-	-	-	-

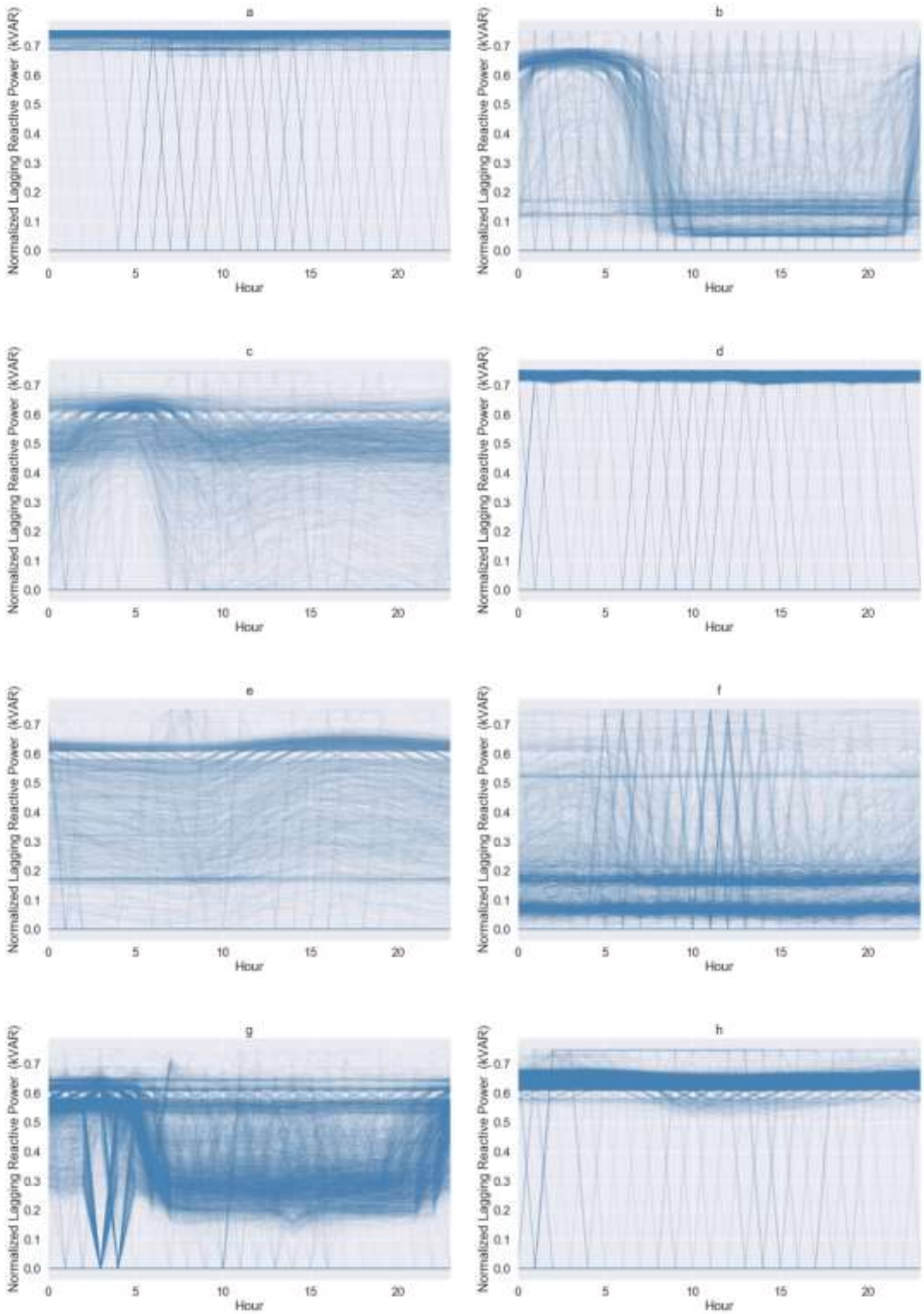
4. Final SARIMAX Model Mean Prediction, RMSE, and MAE for Lagging and Leading Reactive Power Per Site by pu and kVAR

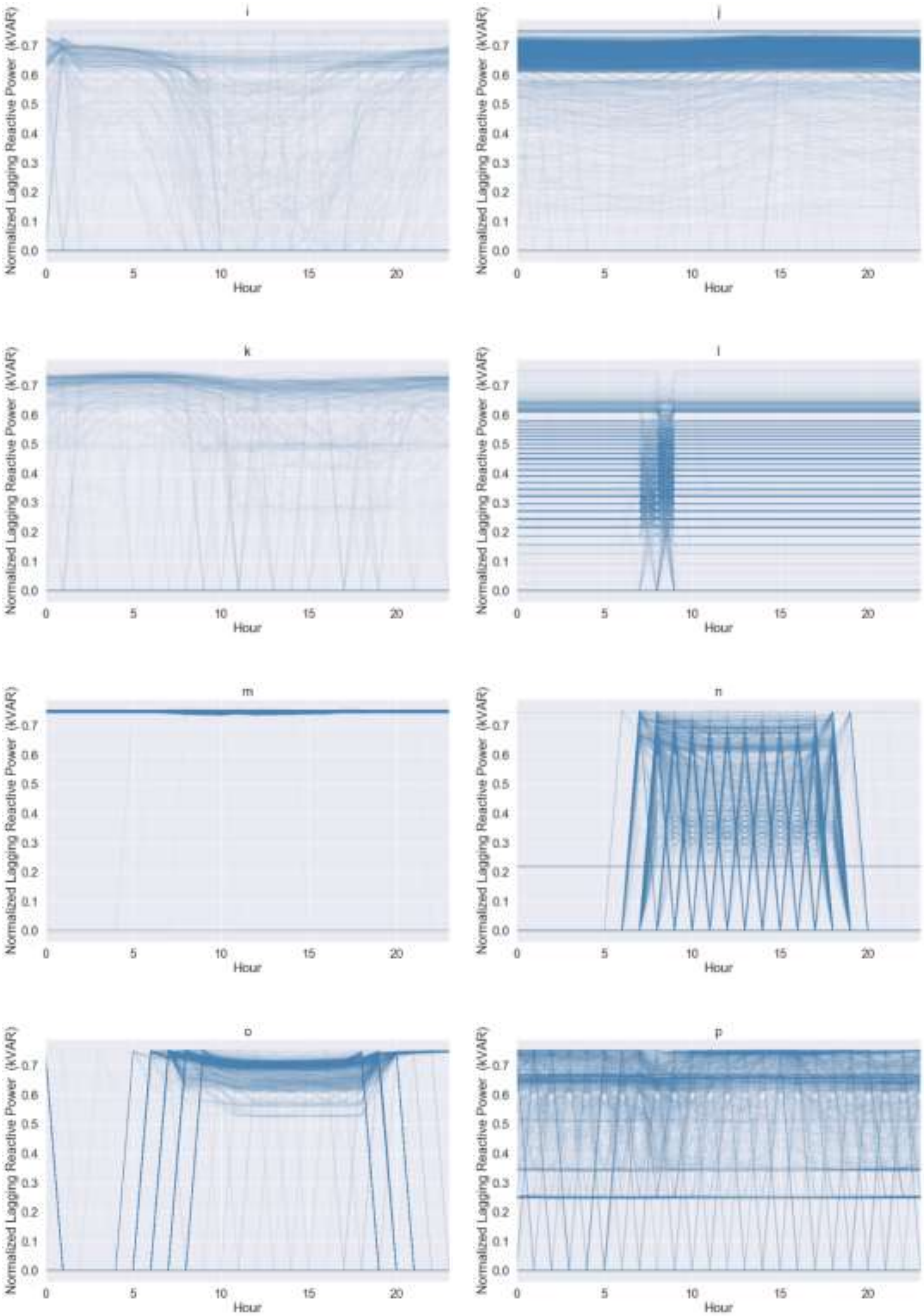
Site	Apparent Power Rating (kVA)	Lagging Reactive Power (pu)			Leading Reactive Power (pu)			Lagging Reactive Power (kVAR)			Leading Reactive Power (kVAR)		
		Mean Prediction	RMSE	MAE	Mean Prediction	RMSE	MAE	Mean Prediction	RMSE	MAE	Mean Prediction	RMSE	MAE
a	153	0.74	0.24	0.12	-0.40	0.14	0.09	113	37	18	-61	21	14
b	2,328	0.53	0.15	0.07	-0.19	0.07	0.04	1,234	349	163	-442	163	93
c	2,122	0.56	0.08	0.03	-0.19	0.05	0.03	1,188	170	64	-403	106	64
d	165	0.71	0.13	0.07	-0.38	0.07	0.04	117	21	12	-63	12	7
e	5,294	0.55	0.11	0.05	-0.20	0.05	0.04	2,912	582	265	-1,059	265	212
f	294	0.53	0.12	0.04	-0.17	0.06	0.03	156	35	12	-50	18	9
g	706	0.55	0.10	0.04	-0.20	0.04	0.02	388	71	28	-141	28	14
h	5,412	0.61	0.11	0.04	-0.26	0.05	0.03	3,301	595	216	-1,407	271	162
i	659	0.58	0.13	0.06	-0.22	0.07	0.04	382	86	40	-145	46	26
j	918	0.68	0.10	0.04	-0.32	0.06	0.04	624	92	37	-294	55	37
k	312	0.58	0.15	0.12	-0.26	0.09	0.08	181	47	37	-81	28	25
l	6,588	0.54	0.09	0.04	-0.19	0.05	0.03	3,558	593	264	-1,252	329	198
m	1,000	0.86	0.04	0.02	-0.51	0.04	0.02	860	40	20	-510	40	20
n	1,882	0.21	0.26	0.16	-0.10	0.12	0.07	395	489	301	-188	226	132
o	2,418	0.35	0.17	0.06	-0.16	0.10	0.05	846	411	145	-387	242	121
p	88	0.62	0.17	0.08	-0.24	0.10	0.07	55	15	7	-21	9	6
q	76	0.72	0.12	0.07	-0.36	0.10	0.06	55	9	5	-27	8	5
r	353	0.65	0.11	0.06	-0.29	0.08	0.06	229	39	21	-102	28	21
s	176	0.62	0.12	0.07	-0.26	0.09	0.07	109	21	12	-46	16	12
t	88	0.59	0.19	0.09	-0.29	0.11	0.08	52	17	8	-26	10	7
u	235	0.63	0.06	0.03	-0.42	0.11	0.05	148	14	7	-99	26	12
v	76	0.64	0.07	0.03	-0.29	0.05	0.04	49	5	2	-22	4	3
w	76	0.66	0.07	0.03	-0.28	0.04	0.02	50	5	2	-21	3	2
x	176	0.73	0.13	0.07	-0.37	0.09	0.06	128	23	12	-65	16	11
y	88	0.69	0.21	0.12	-0.34	0.13	0.08	61	18	11	-30	11	7
z	935	0.74	0.12	0.06	-0.40	0.07	0.03	692	112	56	-374	65	28
aa	118	0.60	0.16	0.05	-0.29	0.08	0.03	71	19	6	-34	9	4
bb	235	0.74	0.21	0.11	-0.38	0.12	0.08	174	49	26	-89	28	19
cc	2,941	0.48	0.20	0.07	-0.24	0.12	0.04	1,412	588	206	-706	353	118

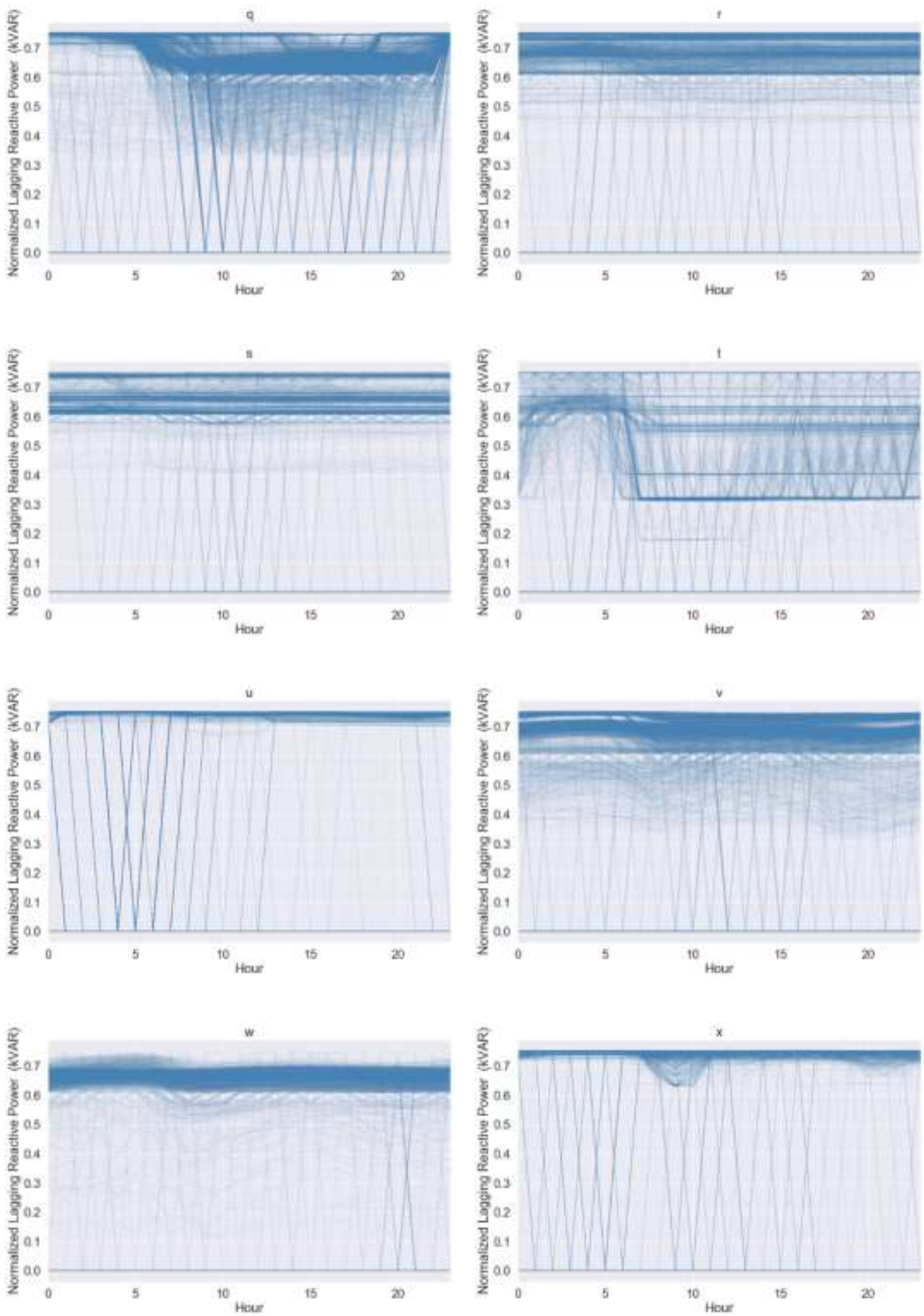
5. Availability of CHP System Reactive Power Per Site

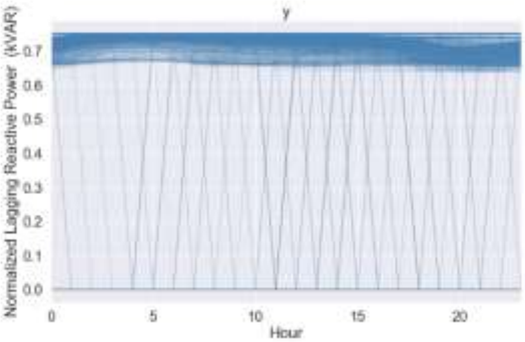
Site ID	Total # Hours	# Hours >0 kWh	Availability
a	34,320	21,350	62%
b	28,177	27,337	97%
c	28,225	27,822	99%
d	35,136	25,452	72%
e	29,857	28,047	94%
f	47,232	44,819	95%
g	70,056	61,623	88%
h	43,585	41,172	94%
i	9,480	7,827	83%
j	54,481	53,990	99%
k	9,480	7,458	79%
l	77,208	73,819	96%
m	33,048	32,927	100%
n	73,008	15,283	21%
o	37,009	15,143	41%
p	34,801	34,604	99%
q	60,409	57,748	96%
r	41,281	39,955	97%
s	35,040	31,425	90%
t	25,345	17,865	70%
u	24,289	22,161	91%
v	55,249	54,223	98%
w	31,897	30,872	97%
x	34,105	24,955	73%
y	37,417	34,259	92%
z	3,720	3,558	96%
aa	25,345	19,005	75%
bb	25,345	23,650	93%
cc	58,416	23,328	40%

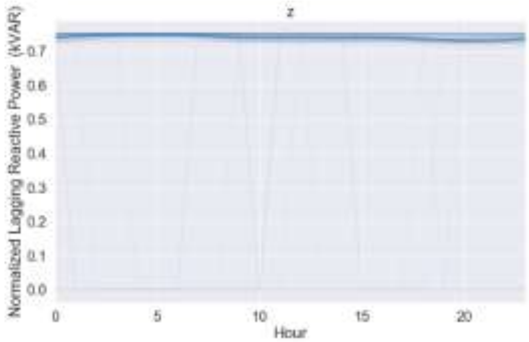
6. Daily Profiles of Lagging Reactive Power




i
j
k
l
m
n
o
p
Normalized Lagging Reactive Power (kVAR)
Hour


q
r
s
t
u
v
w
x
Normalized Lagging Reactive Power (kVAR)
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0
5
10
15
20
Hour


y
Normalized Lagging Reactive Power (kVAR)
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7
0 5 10 15 20
Hour


z
Normalized Lagging Reactive Power (kVAR)
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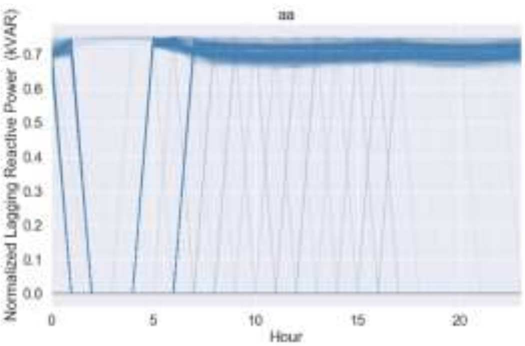
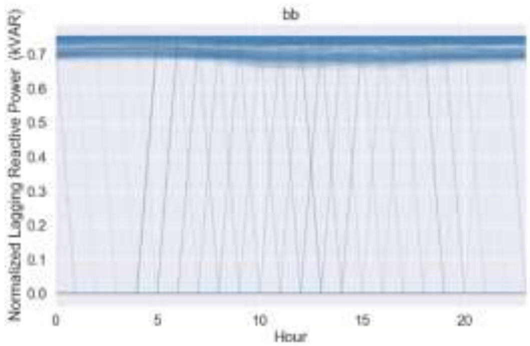
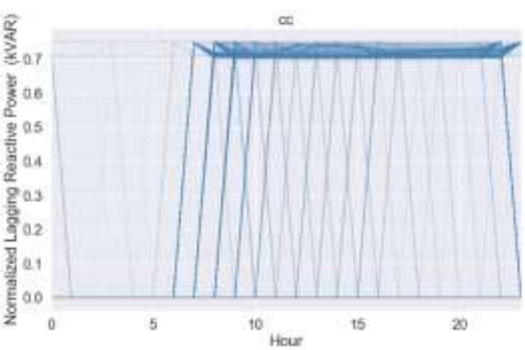
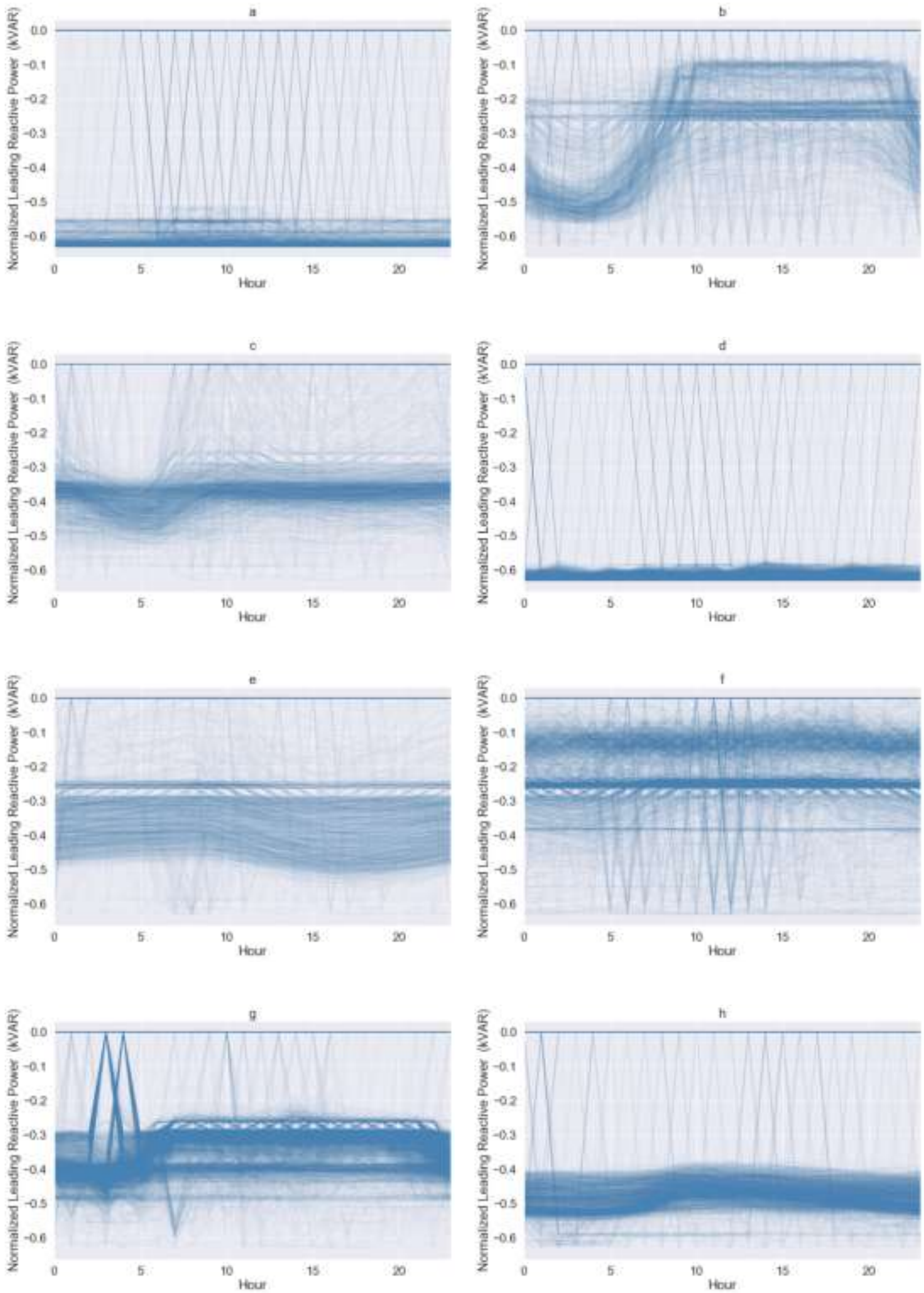
0 5 10 15 20
Hour

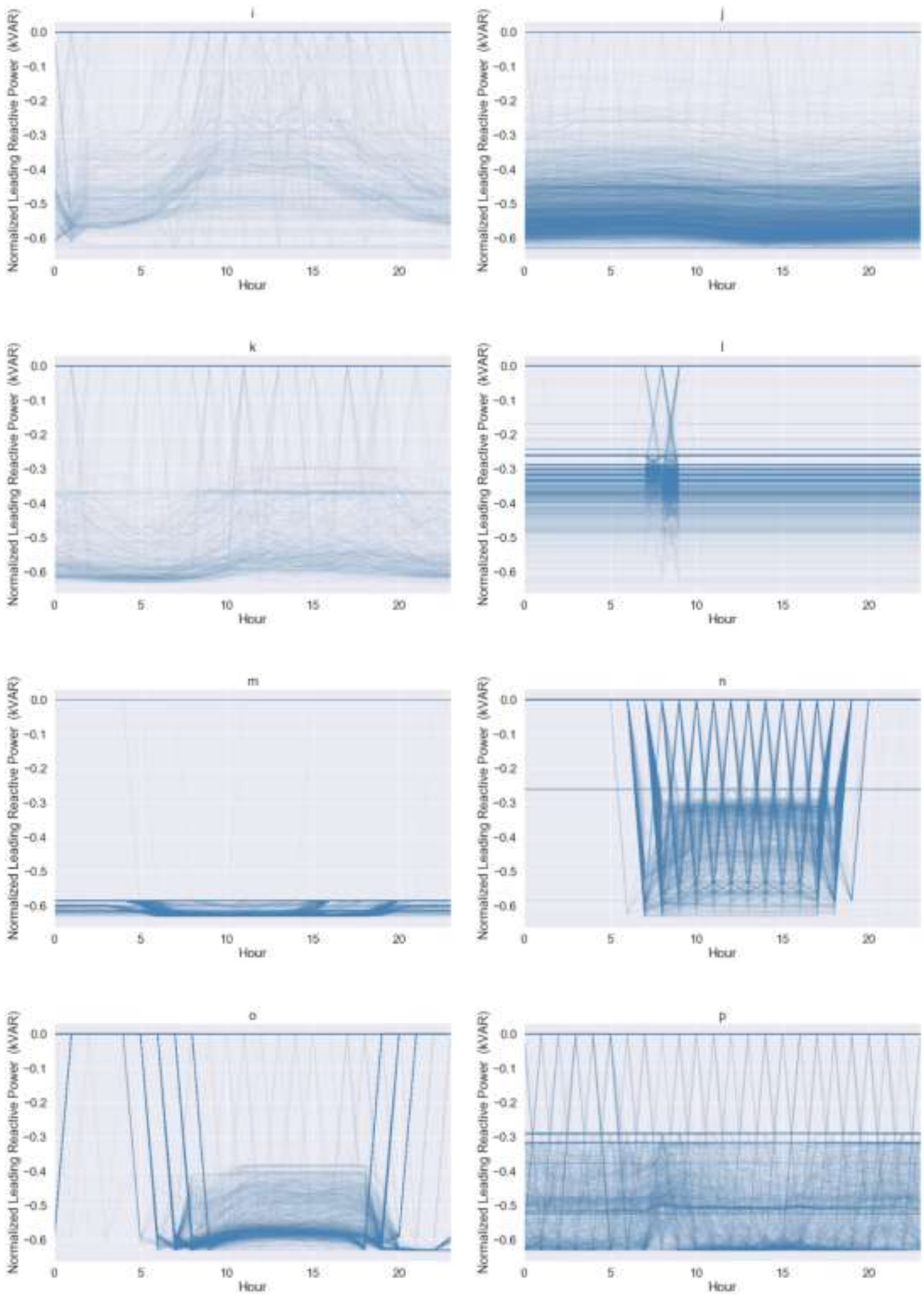

aa
Normalized Lagging Reactive Power (kVAR)
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7
0 5 10 15 20
Hour


bb
Normalized Lagging Reactive Power (kVAR)
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7
0 5 10 15 20
Hour

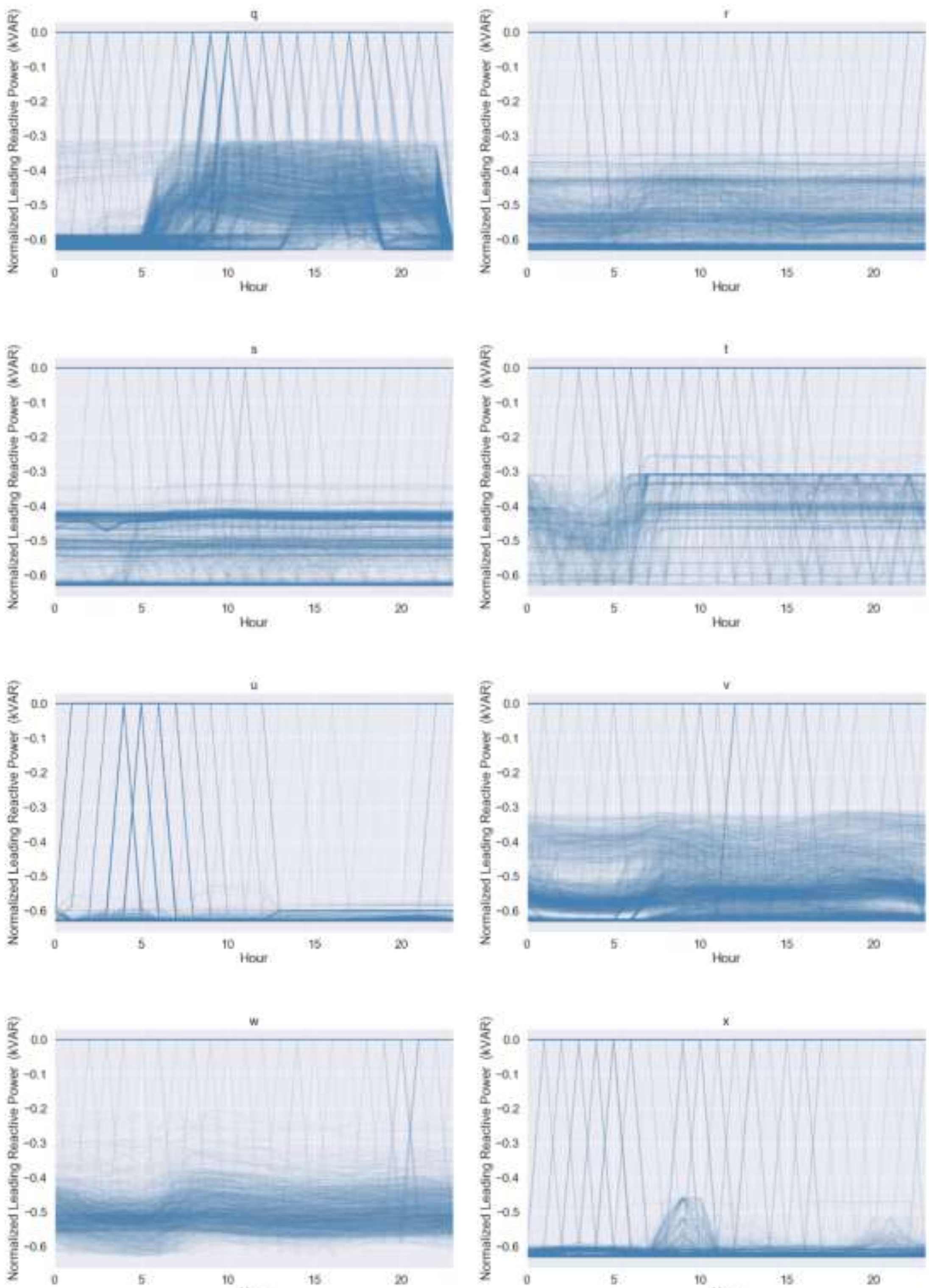

cc
Normalized Lagging Reactive Power (kVAR)
0.0 0.1 0.2 0.3 0.4 0.5 0.6 0.7
0 5 10 15 20
Hour

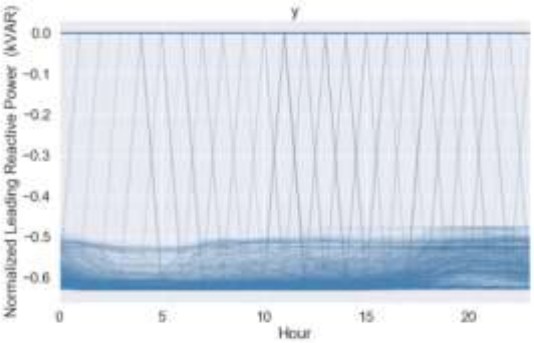
7. Daily Profiles of Leading Reactive Power

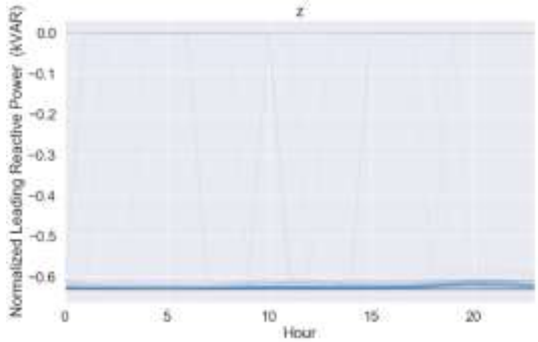


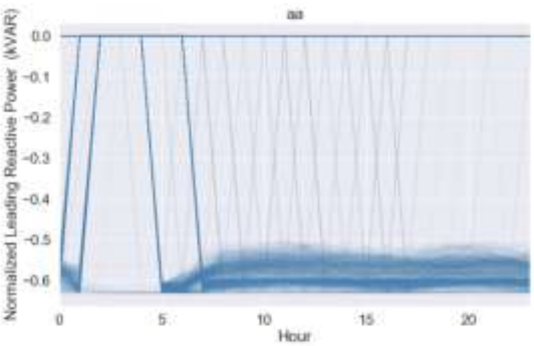


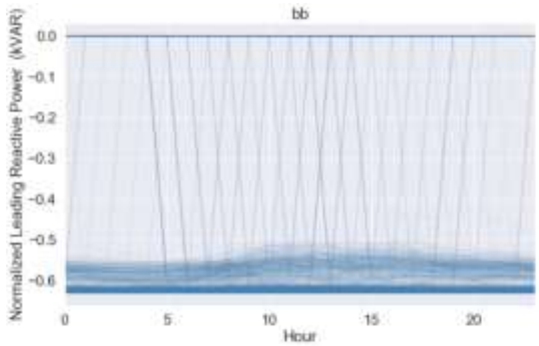
i
j
k
l
m
n
o
p
Normalized Leading Reactive Power (kVAR)
Hour

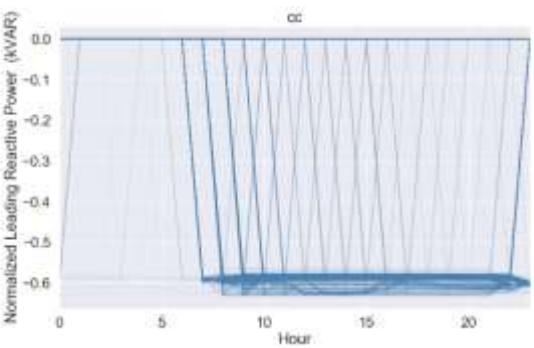

q
r
s
t
u
v
w
x
Normalized Leading Reactive Power (kVAR)
Hour
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
0
5
10
15
20


y
Normalized Leading Reactive Power (kVAR)
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
0
5
10
15
20
Hour


z
Normalized Leading Reactive Power (kVAR)
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
0
5
10
15
20
Hour


aa
Normalized Leading Reactive Power (kVAR)
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
0
5
10
15
20
Hour


bb
Normalized Leading Reactive Power (kVAR)
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
0
5
10
15
20
Hour


cc
Normalized Leading Reactive Power (kVAR)
0.0
-0.1
-0.2
-0.3
-0.4
-0.5
-0.6
0
5
10
15
20
Hour

8. CHP System Reactive Power Operational Cost Assumptions

Category	Scenario 1	Scenario 2	Scenario 3	Source
Fuel cost	$0.12 / therm	$0.28 / therm	$0.55 / therm	[36]
CHP electrical efficiency	42%	34.5%	27%	[18], [37]
Efficiency loss from reactive power	2%	2%	2%	[11], [38]

9. Capacitor Bank Cost Assumptions

Size	Voltage	Year	CapEx	Install	CapEx + Install ($ '20)	Unit CapEx + Install ($'20)	O&M	O&M ($'20)	O&M / kVAR ($'20)	Source
140 kVAR	480 V	2014	$1,600	-	$1,764.54	$12.60 / kVAR	-	-	-	[41]
500 kVAR	480 V	2012	$21,405	$10,000	$31,405.00	$62.81 / kVAR	-	-	-	[42]
200 kVAR	4.16 kV	2016	$4,000	$1,200	$5,662.13	$28.31 / kVAR	$200 / yr	$217.77 / yr	$1.09 / kVAR-yr	[43]
300 kVAR	13.8 kV	2016	$7,500	$1,600	$9,908.73	$33.03 / kVAR	$300 / yr	$326.66 / yr	$1.09 / kVAR-yr	[43]
500 kVAR	5 kV	2012	$1,000	-	$1,138.12	$2.28 / kVAR	-	-	-	[44]
50 MVAR	115 kV	2014	$1,000,000	-	$1,102,836.06	$22.06 / kVAR	-	-	-	[45]
600 kVAR	7.2 kV	2018	$10,000	-	$10,407.64	$17.35 / kVAR	-	-	-	[46]
900 kVAR	-	2016	$13,747*	-	$14,968.71*	$16.63 / kVAR	-	-	-	[47]
5 MVAR	6.6 kV	2006	$22,000*	-	$28,620.08*	$5.72 / kVAR	$3,600 / yr	$4,683.29 / yr	$0.94 / kVAR-yr	[48]
Scenario 1	Min					$2.28 / kVAR			$0.94 / kVAR-yr	
Scenario 2	Average					$22.31 / kVAR			$1.04 / kVAR-yr	
Scenario 3	Max					$62.81 / kVAR			$1.09 / kVAR-yr	

*Includes installation cost

- No cost provided