Journal of Renewable and Sustainable Energy

Open-source multi-year power generation, consumption, and storage data in a microgrid

Cite as: J. Renewable Sustainable Energy **13**, 025301 (2021); https://doi.org/10.1063/5.0038650
Submitted: 24 November 2020 • Accepted: 09 February 2021 • Published Online: 24 March 2021

Sushil Silwal, Colton Mullican, Yi-An Chen, et al.

Journal of Renewable and Sustainable Energy ARTICLE scitation.org/journal/rse

Open-source multi-year power generation, consumption, and storage data in a microgrid

Cite as: J. Renewable Sustainable Energy **13**, 025301 (2021); doi: 10.1063/5.0038650
Submitted: 24 November 2020 · Accepted: 9 February 2021 ·
Published Online: 24 March 2021

View Online Export Citation CrossMark

Sushil Silwal,[a)] Colton Mullican, Yi-An Chen, Avik Ghosh, John Dilliott, and Jan Kleissl

AFFILIATIONS

Center for Energy Research, University of California San Diego, La Jolla, California 92093, USA

[a)]Author to whom correspondence should be addressed: ssilwal@ucsd.edu

ABSTRACT

Open-source, high resolution power consumption data are scarce. We compiled, quality controlled, and released publicly a comprehensive power dataset of parts of the University of California, San Diego microgrid. The advanced microgrid contains several distributed energy resources (DERs), such as solar power plants, electric vehicles, buildings, a combined heat and power gas-fired power plant, and electric and thermal storage. Most datasets contain 15-min averages of real and reactive power from 1 January, 2015 until 29 February, 2020. We also include Python codes to fill missing data and flag and replace potentially erroneous data. The extensive dataset of conventional and new DERs is designed to accelerate research and development work in the area of sustainable microgrids.

I. INTRODUCTION

The modern electrical power grid is undergoing a massive restructuring mostly due to integration of renewable and distributed energy resources (DERs) to reduce our dependence on fossil fuels.[1] This transition of the power grid into a clean energy infrastructure requires extensive research on emerging grid technologies, and it is partly limited by the unavailability of practical energy generation, usage, and storage data.[2,3] This lack of data in the research community is thought to be for two reasons: (i) limited real-world adoption of DERs and (ii) power utilities and customers are not willing to publish their data for public consumption for reasons of privacy and competitiveness.

There are some publicly available DER datasets. Twenty four of the available datasets are reviewed by Kapoor *et al.*[4] Most impactful and notable among them is the Pecan Street data that contain energy usage, EV charging, rooftop solar generation, and energy storage data collected from more than 1000 submetered, mostly residential buildings located in Pecan Street in Texas, with time steps ranging from 1 s to 15 min.[5] The Open Power System Data[6] and ENTOS-E[7] contain aggregated power system data, mostly of European countries, but lack building level and EV data. The work in Ref. 8 presents five years of 1 s power data of a small microgrid with a rooftop solar PV generator (91 kW), lead acid battery storage (326 kWh, 90 kW), an emergency back-up generator, and a single research building. The 1 min energy consumption data of a seven-story office building in Bangkok are collected in Ref. 9 and cover 18 months. All these datasets lack one or more of the following elements, all of which are essential components of most commercially viable microgrids: multiple types of DERs and multiple commercial buildings. We intend to fill this gap in data availability with data from 13 buildings and multiple DERs connected to a microgrid at the University of California (UC), San Diego campus. This will facilitate and accelerate research applying model predictive control and optimization, machine learning, and other statistical methods to microgrid design (e.g., Ref. 10), simulated microgrid operation (e.g., Ref. 11), and smart charging of electric vehicles (e.g., Ref. 12).

The remainder of this work is organized as follows. Section II provides a brief introduction of UC San Diego's microgrid for the context of the collected data. Section III discusses the database. Section IV provides guidelines for filling missing and replacing erroneous data points. Section V concludes the paper with merits of published data.

II. MICROGRID OVERVIEW

The core content of this paper is the power generation, consumption, and storage data from parts of the UC San Diego microgrid. The microgrid serves the main campus at 9500 Gilman Drive, La Jolla, California 92093, and includes the Scripps Institution of Oceanography. UC San Diego has been at the forefront of clean energy solutions.[13] As one of the most advanced microgrids in the world, the UC San Diego hosts a central natural gas fired plant with two high efficiency 13.5 MW combined cycle co-generation Solar Turbines Titan 130 turbines and a 3 MW Dresser-Rand steam turbine, 10 million gallons of chilled thermal energy storage, 3 MW distributed solar PV generators, a 2.8 MW fuel cell that is the largest on a US college campus, 2.5 MW battery energy storage systems, 125 electric vehicle charging stations (many with dual ports), and energy efficient campus buildings with controllable loads. Overall, UC San Diego self-generates about 85% of its electricity consumption and imports the remaining 15% from the local utility, San Diego Gas & Electric (SDG&E).

UC San Diego also operates the 184,025 ft^2 logistics warehouse at 7835 Trade Street, San Diego, California 92121, which acts as the shipping & receiving hub and storage location for the university. It is equipped with a 233 kW solar PV system.

Selected data pertaining to different generators, loads, storage, and grid imports are released in this paper. While there are more metered data available than what is included in this data release—since not all buildings are metered—we believe that a comprehensive dataset would provide relatively little additional value. Most microgrids consist only of a few buildings, and they can be represented with the data released here.

An important caveat for these data is that cooling and heating energy is not included in the building energy use, while the electric power consumed by air handlers for ventilation is included. The campus operates a district heating and district cooling system. Waste heat from the co-generation plant is captured and used to provide heat to campus buildings. Waste heat is also converted to chilled water through absorption chillers. The central chilling capacity is augmented with electric chillers and differences in chilled water supply, and demand can be managed with the thermal energy storage tank. Chilled and hot water consumption to individual buildings is metered, but it is not stored and therefore cannot be provided. As a proxy, we provide volumetric flow rates and temperatures of hot and chilled water supply from the central plant to the entire campus. A detailed description of these data is included in Appendix B.

III. DATA RECORDS

A. Campus operations

The UC San Diego microgrid has utility-grade Schneider Electric ION electricity meters on 70% of the campus' generators, storage systems, grid import, and building loads. These meters monitor energy and power quality and interface with an existing PowerLogic ION Enterprise web-enabled software system. The data are live-streamed to the UC San Diego intranet. The average of the preceding 15 min is archived as a single data point, i.e., a total of 96 data rows are saved per day for each meter. All available data starting from 1 January, 2015 to 29 February, 2020 are downloaded as comma separated value (csv) files. Building loads on a university campus are unique due to the academic year. Depending on the building occupancy, loads can be substantially lower during the summer break, the winter holidays, and spring break as most students and teaching staff will be absent. However, research and department operations continue during academic breaks, except at the end of the year when UC San Diego institutes a complete campus closure for about one week starting around December 24 and ending around January 1. UC San Diego academic calendars are available in Ref. 14.

All data sources are presented in Table 1 and Appendix A, and their physical locations are mapped in Figs. 2 and 3 and Appendix B. These data are broadly classified into seven groups.

B. Buildings

Real and reactive power consumption for the following campus buildings is compiled:

1. Buildings without EV charging

Robinson Hall, Pepper Canyon Hall, Student Services Center, Galbraith Hall, Geisel Library, Center Hall, Social Science Research, Otterson Hall, East Campus Office Building, Economics, Music, and Mandeville Center.

2. Building with EV charging

Hopkins Parking Structure and Police Department. The total load data in the facility are separated into building power and EV charging power consumption data.

A sample building load timeseries is illustrated in Fig. 1. The upper subplot shows the entire real power consumption data for Pepper Canyon Hall with missing data and a potential error marked (see Sec. IV B). The lower subplot shows repetitive daily and weekly power consumption trends.

C. Trade Street Warehouse microgrid

The real net load data for Trade Street Warehouse is from the utility meter, which reports the building load minus the (behind the meter) solar power generation. The Trade Street Warehouse microgrid also includes a 200 kW/400 kWh BESS and a 10 kW V2G EV charging station, both behind the meter. The solar power generated and BEES datasets are also compiled and reported.

D. EV charging stations

As of August 1, 2020, there are 210 ChargePoint EV charging ports of which four are DC fast chargers. These charging stations have been installed over the years since 2017. The EV charging dataset contains transactions from all ChargePoint® stations including charging station details, charging duration with start and end time, and energy consumed. The datasets of the Hopkins Parking Structure in Sec. III B consist of separate aggregate timeseries of EV charging and associated

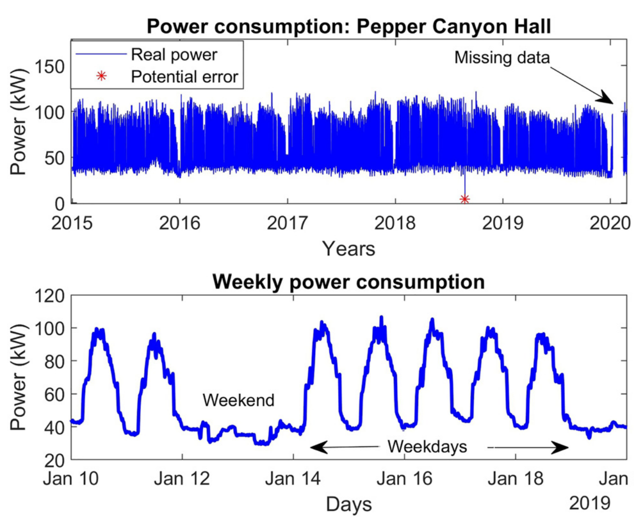

FIG. 1. Real power consumption time series data for the Pepper Canyon Hall campus building for (top) the complete dataset and (bottom) ten days during the academic year.

building power consumption at 15 min resolution, while this section contains individual EV charging events at the Hopkins, Gilman, and Osler Parking Structure. The EV state of charge (SOC) at the beginning of charging is not available but can be backed out following Ref. 12.

E. Solar PV generators

Since all solar inverters operate at the unity power factor following the 2003 IEEE 1547 standard, only real AC power generation data for 26 on-campus PV plants are provided. Some PV systems such as in Leichtag Biomedical Research experienced temporary decreases in power due to unknown hardware issues.

F. Campus thermal load and storage

The microgrid operates a natural gas fired combined heat & power plant that provides district heating and cooling to most buildings on the campus. The plant consists of two 13.5 MW natural gas turbines, a steam generator, electric chillers, and a chilled water tank for thermal energy storage. Since the building electric load data only include fan ventilation power, but not cooling (or heating) load, we include campus-wide chiller plant electricity consumption, chilled water flow, cooling tons, and the chilled water tank capacity.

G. Demand charge related data

Demand charges are peak power charges ($/kW) for the highest monthly consumption in any 15 min interval (non-coincident charges) and the highest consumption during the peak period (1600–2100 h every day). Since the campus has on-site generation, the noncoincident demand charge calculation is complex. Therefore, all data required to calculate demand charges are included in this section. This includes the SDG&E real power import (which is the relevant data for peak demand charges), on-campus generation (to compute the actual campus demand), and adjusted demand (to compute noncoincident demand charges).

H. Battery energy storage system (BESS)

UC San Diego owns a 2.5 MW, 5 MWh BESS, which has primarily been used for demand charge management. Starting July 1, 2020, the BESS also occasionally participates in the California Independent System Operator (CAISO) demand response auction market. The load power consumed while charging the battery is represented in positive kW, and the generated power during discharging operation is represented in negative kW.

IV. MISSING DATA AND DATA QUALITY CONTROL

A. Missing data

Missing data fractions are shown in Table I and Appendix A. Since redundant meters are not available, the actual values for the missing data points are unknown and an imputation model is required. Reasons for missing data are as follows: (i) meter outage, (ii) data loss during transmission from meter to meter server, or (iii) meter server error. Consistent with the commercial operation of the meters, the reasons for missing data have not been logged and are unknown. A simple imputation algorithm based on persistence will be discussed in Subsection V and is provided with the data.

Python scripts to find and fill the missing data and outliers as tabulated in Table II and Appendix A are provided in the repository alongside the raw datasets.

B. Data quality control

Data quality control was also conducted. Since building loads result from the actions of hundreds of human occupants and automated building controllers, data errors are difficult to ascertain. Generally, errors in industrial grade electric meters are highly unlikely and small. Nevertheless, the database is checked for incorrectly recorded data based on unusual values (data range) and unusual changes in values (data ramps). Usually—with the exception of solar power and BESS data where cloud cover can induce large ramps over 15 min intervals—power generation, load, and thermal storage data follow daily, weekly, or yearly periodicity and experience only small ramps. Thus, sudden large ramps for a brief period of time and large deviations from the periodic pattern may be erroneous unless they can be explained by corresponding physical events such as a fault. Erroneous data points are located as follows:

- Step I: Since all buildings have persistent loads such as lighting and plug loads, electric power is never zero. Except for PV generators and BESS, zero readings or close to zero (<2 kW) are marked as NaN data points. The reactive power consumption data for Hopkins Parking Structure is exempted from this recommendation as there are data points around zero.
- Step II: Filter the data using a Gaussian filter with a suitable window size in the range of 10–25. The Gaussian filter is chosen for smoothing the data such that an actual data point sufficiently far from the expected value can be categorized as the outlier. The window size (which is called the "standard deviation" in the python code) and distance from the expected value are calibrated iteratively such that outliers are detected with high confidence.
- Step III: Locate outliers that are sufficiently far from the filtered data: Let $P(t)$ be raw data and $\tilde{P}(t)$ be filtered data at time t. If $|P(t) - \tilde{P}(t)| > P_t$, then $P(t)$ is flagged. The flagged data points are visually examined, and the permissible threshold P_t is recalibrated such that the remaining outliers can be categorized as errors with high confidence. Figure 1 shows an example of an error for the Pepper Canyon Hall real power consumption data. A total of 235 possible error data points are identified across all the datasets, which can be replaced with suitable values as described in Sec. V.

V. FILLING MISSING DATA AND REPLACING OUTLIERS

The NaN, missing, or erroneous data points are replaced or filled with the most recent valid data at the same time of day from the nearest earlier day of the same type (business or non-business). For instance, a data error at 1500 on Monday is replaced by data at 1500 on the preceding Friday (assuming that both days are business days). If the missing data source day is unavailable, which was the case during a few days at the beginning of the dataset in early January 2015, the missing data and outliers are replaced with the most recent valid data. Since both raw and quality-controlled data are provided, the user can apply their own imputation methods.

The data quality control methods are basic but allow users to quickly generate complete data for a period of around 5 years, which—given the relatively small amount of missing data and outliers—will suffice for many applications such as microgrid sizing and dispatch. In certain research areas such as forecasting, the data quality control methods presented here may not be acceptable and researchers should, then, only use complete subsets of the data or write their own code with sophisticated algorithms to populate the missing data points.

VI. CONCLUSIONS

We have compiled and released power system data of diverse generation, consumption, and storage devices of the UC San Diego microgrid. These includes datasets for buildings and building complexes, EV charging stations, solar PV generators, and thermal energy storage and load. Furthermore, the total power generation at UC San Diego, imported power from local utility, adjusted UC San Diego demand load, and UC San Diego peak demand are also included to facilitate research in demand charge reduction. Recognizing the rarity of large scale power system data in the scientific community, we intend to serve the data needs of fellow researchers and accelerate research and development work in the area of sustainable power grids. Researchers in the area of emerging grid applications, especially optimization or forecasting studies, will benefit from the published data.

SUPPLEMENTARY MATERIAL

See the supplementary material for datasets and scripts as described in Appendix A are the crux of the paper and are released under a Creative Commons (CC) license at the open-access repository at https://github.com/sushilsilwal3/UCSD-Microgrid-Database.

ACKNOWLEDGMENTS

The authors would like to thank the UC San Diego Vice Chancellor of Resource Management and Planning Gary Matthews, the Associate Vice Chancellor Steve Jackson, the Director of Strategic Energy Initiatives Byron Washom, the Energy & Utilities manager John Dilliott, and the facility management team including Robert Austin and others for publishing the data to the campus community and for allowing us to release the data.

APPENDIX A: DATA REPOSITORY AND CODE

All data and Python codes are tabulated in Table I. All numerical data files are in comma separated values (.csv) format. Missing

TABLE I. Metadata of the released data. Unk—unknown and NA—not applicable.

Facility/function	PV (DC, AC kW) or Battery Rating	Data file name	Start date	End date	Missing days
EV charging stations	NA	Chargepointev	15 March, 2016	29 Feb, 2020	None
Thermal load/storage	NA	Thermalstorage.csv	12 May, 2016	29 Feb, 2020	None
Demand charges	NA	Demandcharge.csv	01 Jan, 2015	29 Feb, 2020	none
BYD battery energy storage	2.5 MW, 5.0 MWh	Batterystorage.csv	30 Nov, 2015	29 Feb, 2020	8.1
Campus Buildings					
Robinson Hall	NA	Robinsonhall.csv	01 Jan, 2015	29 Feb, 2020	412.8
Pepper Canyon Hall	NA	Peppercanyon.csv	01 Jan, 2015	29 Feb, 2020	36.5
Student Service Center	NA	Studentservices.csv	05 April, 2016	29 Feb, 2020	58.9
Social Sciences	NA	Socialscience.csv	01 Dec, 2016	29 Feb, 2020	0.5
Galbraith Hall	NA	Galbraithhall.csv	01 Jan, 2015	29 Feb, 2020	0.4
Geisel Library	NA	Geisellibrary.csv	29 Aug, 2017	29 Feb, 2020	0.2
Center Hall	NA	Centerhall.csv	07 Jan, 2016	29 Feb, 2020	0.25
East Campus Office	NA	Eastcampus.csv	08 July, 2017	29 Feb, 2020	0.2
Mandeville Center	NA	Mandeville.csv	01 Jan, 2015	29 Feb, 2020	1.2
Hopkins Parking Building	NA	Hopkinsbuilding.csv	01 April, 2019	01 Jan, 2020	None
Hopkins Parking EV	NA	Hopkinsev.csv	01 April, 2019	01 Jan, 2020	None
Police Department Building	NA	Policebuilding.csv	01 June, 2020	10 Oct, 2020	None
Police Department EV	NA	Policeev.csv	01 June, 2020	10 Oct, 2020	None
Otterson Hall	NA	Ottersonhall.csv	01 Jan, 2015	29 Feb, 2020	265.4
Music Building	NA	Musicbuilding.csv	28 Aug, 2015	29 Feb, 2020	0.2
Rady Hall	NA	Radyhall.csv	12 Feb, 2015	29 Feb, 2020	0.4
Trade Street Off-campus Microgrid					
Trade Street Warehouse	NA	Tradestreettotal.csv	31 Aug, 2016	26 July, 2019	25.6
Trade Street PV	233, Unk	Tradestreetpv.csv	08 Feb, 2016	29 Feb, 2020	38.6
Trade Street Battery	200 kW, 400 kWh	Tradestreetbattery.csv	25 Oct, 2016	09 Sep, 2018	38.6
On-Campus Solar PV Generators					
Biomedical Sciences Library	Unk, 390	Bsb_librarypv.csv	21 Jan, 2015	29 Feb, 2020	0.5

TABLE I. (*Continued.*)

Facility/function	PV (DC, AC kW) or Battery Rating	Data file name	Start date	End date	Missing days
Biomedical Sciences Building	284, Unk	bsb_buildingpv.csv	21 Jan, 2015	30 Aug, 2018	0.2
Bio-Engineering Hall	Unk, 74	Bioengineeringpv.csv	21 Jan, 2015	29 Feb, 2020	26.7
Campus Service Complex	Unk, 54	Csc_buildingpv.csv	15 Jan, 2016	29 Feb, 2020	49.4
Central Utility Plant	Unk, 65	Cup_pv.csv	01 Jan, 2015	29 Feb, 2020	0.4
Engineering Building Unit II	43, 35	Ebu2_a_pv.csv	27 April, 2015	29 Feb, 2020	0.3
Engineering Building Unit II	37, 31	Ebu2_b_pv.csv	27 April, 2015	29 Feb, 2020	0.3
Electric Shop	Unk, Unk	Electricshoppv.csv	24 Oct, 2015	29 Feb, 2020	0.2
Fleet Services	29, 24	Garagefleetspv.csv	18 Mar, 2016	29 Feb, 2020	0.4
Gilman Parking	195, 200	Gilmanparkingpv.csv	09 May, 2015	29 Feb, 2020	812.1
Hopkins Parking	338, 350	Hopkinsparkingpv.csv	29 Aug, 2015	29 Feb, 2020	1.0
Keeling Apartments	41, Unk	Keelinga_pv.csv	15 May, 2017	29 Feb, 2020	0.1
Keeling Apartments	Unk, Unk	Keelingb_pv.csv	15 May, 2017	29 Feb, 2020	0.1
Otterson Hall	18, Unk	Kyoceraskylinepv.csv	14 Feb, 2016	29 Feb, 2020	200.7
Leichtag Biomedical Research	Unk, 50	Leichtagpv.csv	01 Jan, 2015	29 Feb, 2020	0.3
MESOM Laboratory	61, Unk	Mesom_pv.csv	31 Mar, 2016	29 Feb, 2020	14.3
Mayer Hall	Unk, 120	Mayerhallpv.csv	01 Jan, 2015	29 Feb, 2020	0.4
Oslar Parking	268, Unk	Oslerparkingpv.csv	17 Dec, 2018	29 Feb, 2020	185.4
Price Center	63, 75	Pricecentera_pv.csv	27 April, 2015	29 Feb, 2020	0.3
Price Center	66, 75	Pricecenterb_pv.csv	23 May, 2015	29 Feb, 2020	0.2
SD Supercomputing Center	Unk, 65	Sdsc_pv.csv	01 Jan, 2015	29 Feb, 2020	0.3
Structural and Material Engineering	Unk, 120	Sme_solarpv.csv	14 Oct, 2016	29 Feb, 2020	0.1
Powell Structural Research Lab	6.5, Unk	Powellpv.csv	01 Jan, 2015	03 Mar, 2016	0.1
Birch aquarium	49, Unk	Stephenbirchpv.csv	12 April, 2016	29 Feb, 2020	0.1

data entries are left unfilled, and outliers as identified per Sec. IV B are marked as NaN.

We have included Python codes as tabulated in Table II. The codes read the data, find outliers, and replace outliers and missing data points with a suitable value as described in Sec. V.

APPENDIX B: PHYSICAL LOCATION OF DATA SOURCES

The building locations are shown in Fig. 2, and the solar PV generator locations are shown in Fig. 3.

TABLE II. Python scripts to find and impute missing data and find potential outliers. Since the thermal storage, EV charging, and demand charge data are already provided in a quality controlled form, no Python script is provided. In the EV charging dataset, charging events with 0 kWh consumption were removed as they were likely caused by operator error.

Script file name	Corresponding data
PythonBuildingLoad.py	Building load and trade street total
PythonPVGenerator.py	Solar PV generator
PythonBatteryStorage.py	Campus/trade street battery storage

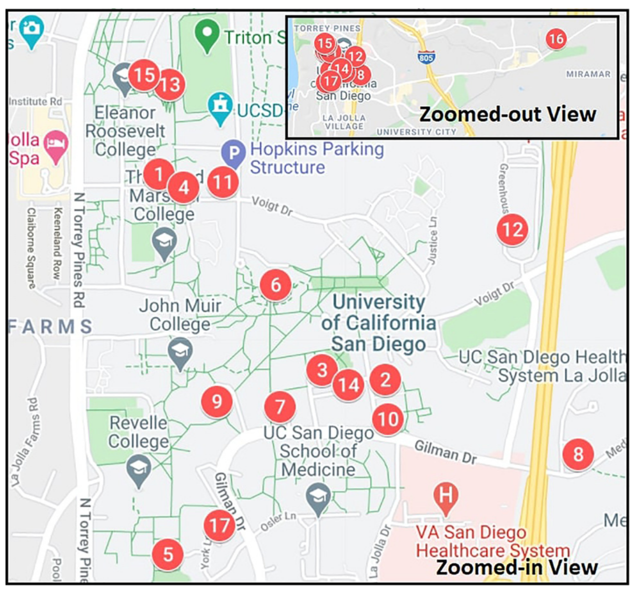

FIG. 2. Location of buildings and facilities: (1) Robinson Hall, (2) Pepper Canyon Hall, (3) Student Services Center, (4) Social Sciences, (5) Galbraith Hall, (6) Geisel Library, (7) Center Hall, (8) East Campus Office, (9) Mandeville Center, (10) Gilman Parking, (11) Hopkins Parking, (12) Police Department, (13) Otterson Hall, (14) Music Building, (15) Rady Hall, (16) Trade Street Warehouse, and (17) Central Utility Plant.

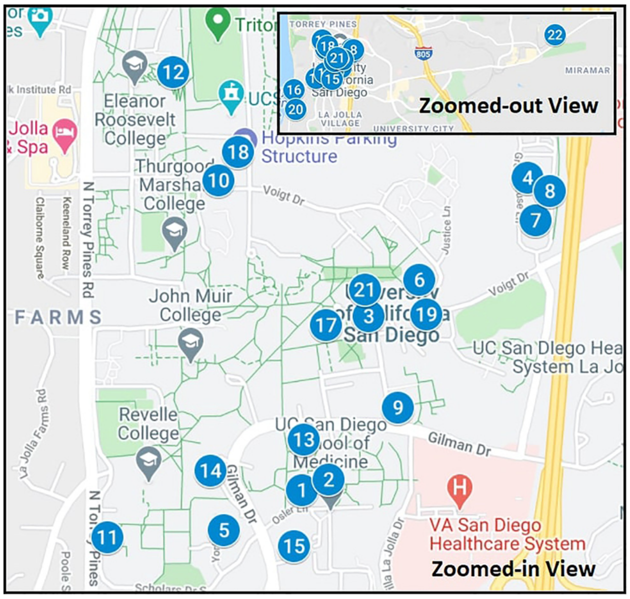

FIG. 3. Location of PV generators: (1) Biomedical Sciences Library, (2) Biomedical Sciences Building, (3) Bio-engineering Hall, (4) Campus Services Complex, (5) Central Utility Plant, (6) Engineering Building Unit II, (7) Electric Shop, (8) Fleet Services, (9) Gilman Parking, (10) Hopkins Parking, (11) Keeling Apartments, (12) Otterson Hall, (13) Leichtag Biomedical Research, (14) Mayer Hall, (15) Osler Parking, (16) MESOM Laboratory, (17) Price Center, (18) SD Supercomputing Center, (19) Structural and Material Engineering, (20) Birch Aquarium, (21) Power Structural Research Lab, and (22) Trade Street Warehouse.

APPENDIX C: DISTRICT COOLING ANALYSIS FOR UC SAN DIEGO

UC San Diego uses district heating and cooling for building thermal regulation. Due to mild temperatures and prevalence of office buildings with large internal heat generation from equipment and people, the district heating system uses significantly less energy than the district cooling system. Therefore, this analysis focuses on the district cooling system. The district cooling system consists of a combined heat and power plant (CHP), a thermal energy storage (TES) tank, and pipes that connect the tank to the campus buildings. Electric chillers are available to augment cooling capacity during peak times. All variables are metered using a Schneider ION metering system. The data streams are shown in Table III. The purpose of this document is to describe this database, provide consistency checks/validations, and present a modified data file that contains the key variables.

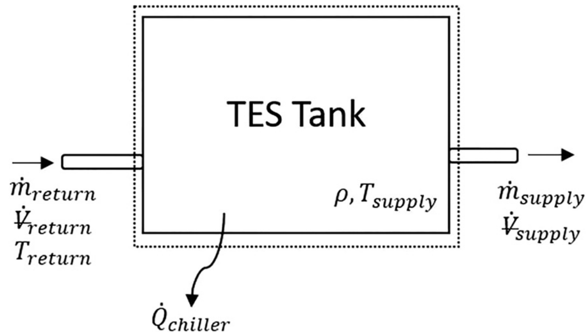

FIG. 4. Thermodynamic analysis of the chilled water loop with the control volume being the thermal energy storage tank.

All thermodynamic processes and variables are illustrated in Figs. 4 and 5. Figure 5 shows a thermodynamic analysis of the TES tank. The TES tank is cooled by the electric chiller and by an absorption chiller attached to the cogeneration plant. It loses heat to campus buildings through the chilled water loop as manifested by the difference in supply and return flow temperatures.

The TES tank is a closed system. Therefore, the mass flow rate of water supplied from the TES is equal to the mass flow rate of water returned to the TES, i.e., $\dot{m}_{supply} = \dot{m}_{return}$. The conservation of energy dictates that

TABLE III. Variable names in the UC San Diego campus data files, derived variables, and input parameters related to thermal states and processes.

Variable name	Units	Definition	Variable name in data file
ρ	lb/gallon	Density of water = 8.343 lb/gallon	N/A
$h_{\text{return}}, h_{\text{supply}}$	BTU/lb	The enthalpy value as determined by the return/supply temperature of the water at the TES. $h_{\text{return}} = 10.72$ BTU/lb and $h_{\text{supply}} = 21.07$ BTU/lb	N/A
$\dot{Q}_{\text{TES}}$	BTU/h	Total chilling power provided to campus buildings from the thermal energy storage tank	CHW MBTU
$\dot{Q}_{\text{chiller}}$	BTU/h	Total chilling power provided to the TES tank from the electric chiller	N/A
$\dot{m}_{\text{supply}}, \dot{m}_{\text{return}}$	lb/h	Mass flow rate of water supplied from the TES to the campus buildings/returned to the TES tank	N/A
$\dot{V}_{\text{supply}}$	Gallons/h	Volumetric flow rate of water supplied from the TES to the campus buildings	CHW supply flow
$\dot{V}_{\text{return}}$	Gallons/h	Volumetric flow rate of water returned to the TES	CHW return flow

TABLE III. (*Continued.*)

Variable name	Units	Definition	Variable name in data file
$\dot{W}_{\text{chiller,in}}$	BTU/h	Chiller electric power consumption (work)	Total chiller plant Elec.
N/A	Tons	Cooling capacity of the TES return flow	Tot CHW Tons (Ret Flo)
N/A	Tons	Cooling capacity of the TES supply flow	Tot CHW Tons (Sup Flo)
$\dot{Q}_{\text{buildings}}$	BTU/h	The respective heat energy contribution to the chilled water flow from each main campus neighborhood	N/A

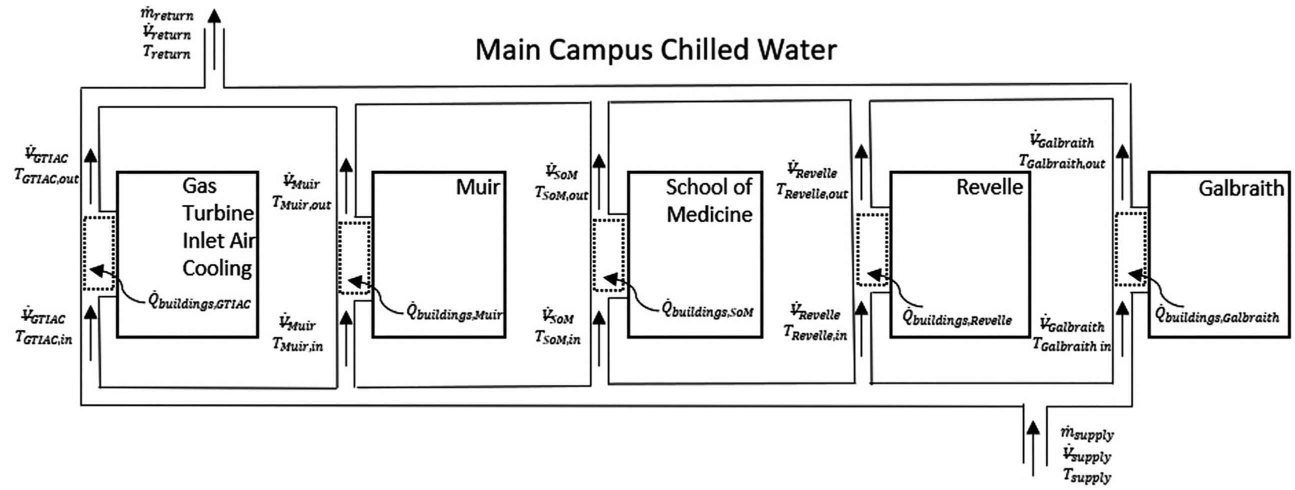

FIG. 5. Architecture and thermodynamic layout of the district cooling system. Control volumes cover the chilled water flow and heat exchange in the campus neighborhoods. The flow through each neighborhood is treated as a closed, steady state system. Heat is produced in the building through solar heating through windows, conduction through the envelope, human body heat, and dissipated heat from electric power consumption. In the steady state, the net heat from the building processes is added to the system through a heat exchanger at each building.

$$\frac{dE_{\text{TES}}}{dt} = \dot{Q}_{\text{chiller}} + \dot{m}_{\text{return}} h_{\text{return}} - \dot{m}_{\text{supply}} h_{\text{supply}}, \quad \text{(C1)}$$

where E_{TES} is in BTU/hour, $\dot{m}_{\text{return/supply}}$ are in lb/hour, and $h_{\text{return/supply}}$ is the enthalpy of water in BTU/lb.

Figure 5 shows the thermodynamic states and processes in the chilled water loop. The chilled water loop splits into five different pipes. One pipe serves to cool the air at the gas turbine inlet. The remaining four pipes serve different neighborhoods of the campus (Muir, School of Medicine, Revelle, and Galbraith). Within each neighborhood, the cooling system of each building dumps heat into the chilled water through a heat exchanger.

Given the closed system in Fig. 5, $\dot{m}_{\text{supply}} = \dot{m}_{\text{return}}$. The conservation of energy yields

$$\frac{dE_{\text{neighborhood}}}{dt} = \dot{Q}_{\text{buildings}} + \Sigma \dot{m}_i h_{i,in} - \Sigma \dot{m}_i h_{i,out}, \quad \text{(C2)}$$

where $\dot{Q}_{buildings}$ is the heat energy added to the control volumes by all buildings in all neighborhoods in BTU/hour, $\dot{m}_i$ is the mass flow rate through each neighborhood's control volume i in lb/gallon, and $h_{i,in/i,outlet}$ is the enthalpy of saturated water in BTU/lb as determined from the given temperature. The sum over i represents the sum over the five control volumes for the neighborhoods. Assuming the control volume to be in a steady state, we take $\frac{dE_{\text{neighborhood}}}{dt} = 0$ and solve for $\dot{Q}_{\text{buildings}}$ as follows:

$$\dot{Q}_{buildings} = \Sigma \dot{m}_i h_{i,out} - \Sigma \dot{m}_i h_{i,in}. \quad \text{(C3)}$$

DATA AVAILABILITY

This paper is based on the raw data collected at the UC San Diego, and the data are released publicly as a supplementary material to the paper.

REFERENCES

[1]M. Moretti, S. N. Djomo, H. Azadi, K. May, K. De Vos, S. Van Passel, and N. Witters, "A systematic review of environmental and economic impacts of smart grids," Renewable Sustainable Energy Rev. **68**, 888–898 (2017).

[2]V. Potdar, A. Chandan, S. Batool, and N. Patel, "Big energy data management for smart grids-issues, challenges and recent developments," in *Smart Cities* (Springer, 2018), pp. 177–205.

[3]K. Moharm, "State of the art in big data applications in microgrid: A review," Adv. Eng. Inf. **42**, 100945 (2019).
[4]S. Kapoor, B. Sturmberg, and M. Shaw, "A review of publicly available energy data sets," Wattwatchers' My Energy Marketplace (MEM) (The Australian National University, Canberra, Australia, 2020).
[5]P. Street, *Dataport: The World's Largest Energy Data Resource* (Pecan Street Inc, 2015).
[6]Open Power System Data, see https://open-power-system-data.org/data-sources for "Data Sources."
[7]ENTSO-E, see https://www.entsoe.eu/data/power-stats/ for "Power Statistics."
[8]K. Vink, E. Ankyu, and M. Koyama, "Multiyear microgrid data from a research building in Tsukuba, Japan," Sci. Data **6**, 190020 (2019).
[9]M. Pipattanasomporn, G. Chitalia, J. Songsiri, C. Aswakul, W. Pora, S. Suwankawin, K. Audomvongseree, and N. Hoonchareon, "Cu-bems, smart building electricity consumption and indoor environmental sensor datasets," Sci. Data **7**, 1–14 (2020).
[10]K. Fahy, M. Stadler, Z. K. Pecenak, and J. Kleissl, "Input data reduction for microgrid sizing and energy cost modeling: Representative days and demand charges," J. Renewable Sustainable Energy **11**, 065301 (2019).
[11]M. Ross, C. Abbey, F. Bouffard, and G. Joós, "Microgrid economic dispatch with energy storage systems," IEEE Trans. Smart Grid **9**, 3039–3047 (2018).
[12]G. C. Wang, E. Ratnam, H. V. Haghi, and J. Kleissl, "Corrective receding horizon EV charge scheduling using short-term solar forecasting," Renewable energy **130**, 1146–1158 (2019).
[13]B. Washom, J. Dilliot, D. Weil, J. Kleissl, N. Balac, W. Torre, and C. Richter, "Ivory tower of power: Microgrid implementation at the University of California, San Diego," IEEE Power Energy Mag. **11**, 28–32 (2013).
[14]UC San Diego, see https://blink.ucsd.edu/instructors/resources/academic/calendars/2020.html for "Academic Calender."