APPENDIX C

FILED
01/20/23
02:45 PM
R2110002

California Public Utilities Commission

January 20, 2023

Energy Division Staff Proposal for Proceeding R.21-10-002

Proposal for Derating Thermal Power Plants based on Ambient Temperature

Prepared by Energy Division Staff

Robert Hansen, PE

Contents

I. Introduction

The Energy Resource Modeling Team (ERM Team) proposes a new method for derating thermal powerplants based on forecast ambient temperatures, and requests approval for its use in planning activities. We are proposing implementing this method in future CPUC modelling efforts that are used to produce analyses for the CPUC Resource Adequacy Proceeding R.21-10-002.

1. Background

The ERM Team uses Strategic Energy & Risk Valuation Model (SERVM) developed by Astrapé Consulting to forecast energy prices and grid reliability under various scenarios. These forecasts inform California Public Utilities Commission's decision-making processes regarding utility rates, capital projects, and programs across various proceedings, including the Resource Adequacy and Integrated Resource Planning proceedings.

SERVM uses numerous input data sources, including the capacities of generation facilities for each scenario. The input capacities for thermal power plants (i.e., gas turbine, combined cycle, and cogeneration) which the ERM Team currently applies in SERVM scenarios, are modeled as being insensitive to environmental factors—available capacities are assumed constant, unvaryingly equal to each plant's rated capacity, and independent of ambient temperature. This static capacity has created minor inconsistencies with current operation, as power plants are currently impacted by high temperature under the current climate regime. However, in a warming climate scenario, the ranges of ambient temperatures under which generators operate are projected to increase, and this may exacerbate the inconsistency between real operating conditions and modeled outcomes in planning studies. That inconsistency could potentially lead to underestimating forecast reliability risks associated with extreme temperatures. In response to these inconsistencies, the ERM Team has developed a methodology to account for the impact of climate change and its concomitant impact on ambient temperatures on the effective capacity of thermal generators. We are proposing this model for use in CPUC Resource Adequacy Proceeding R.21-10-002.

The proposed model is based on literature and findings relevant to California's regulatory framework and SERVM's input data structures. Synthetic temperature profiles will be developed that account for the impacts of climate change (CPUC Staff 2022), which will then be used to modify effective generator capacities under changing ambient temperature conditions in our SERVM model.

The model presented in this proposal aims to satisfy the following criteria:

- Grounded in scientific principles;
- Matches real-world performance of thermal power plants;
- Flexible to use with a variety of generation resources;
- Simple to understand; and
- Integrates with SERVM.

The proposed model consists of a piecewise-linear derating framework based on the academic literature regarding turbine dynamics as discussed in Section II. In Section III, we present a method by which the proposed model parameters are calibrated according to recorded curtailments due to ambient temperatures using data from CAISO. Finally, Section IV discusses the calibrated piecewise-liner model we propose to use in our reliability models.

2. Expected Effects

Applying the proposed model will result in lower forecast available capacities from thermal power plants compared to the currently used model which does not derate capacities based on weather. Forecast derated capacities are expected to range from 90% to 100% of the rated capacity. We propose implementing the derate model only for Combustion Turbine and Combined Cycle resources at this time, using the current-climate weather data for the RA proceeding. Later this year, we plan to use climate-informed weather forecasts reflective of climate change to test a forecast of future capacity availability.

Figure 1 shows monthly statistics for forecast derates for combustion turbines near a weather station in Sacramento (KSAC) based on historic weather data from 1998 through 2020. This chart shows quartiles, 1st, and 99th percentile derates across all 23 years. As expected, the derates are small in the winter months and greater during the summer. The 1st percentile derates depicted at the bottom of the red area represent unusually high temperatures for the given month and drop as low as 92%, while the 99th percentile derates at the top of the dark blue area represent very low temperatures and don't fall below 97%. 50th percentile derates, shown as the boundary between the orange and light blue areas, correspond to median temperatures, and, for this weather station, stays between 95% and 100%. Note that the model limits forecast capacity to a maximum of 100%, resulting in the significant skew toward lower capacities during winter months when derated capacities are most likely to be truncated.

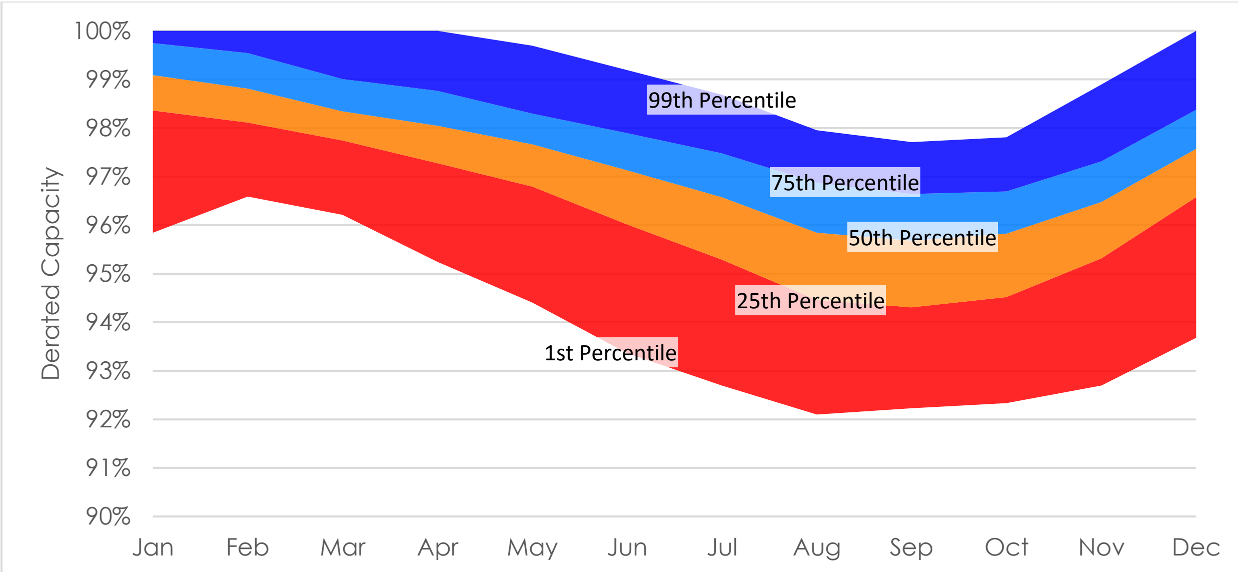

Figure 1 – Monthly Percentile Modeled Ambient Derates for Combustion Turbines near Sacramento based on Weather Years 1998-2020

Figure 2 below presents the distribution of predicted derates across the 24 instances of August across all historical weather years. The ranges of percentiles are shown as colored horizontal lines matching the areas in Figure 1, representing a slice through August in the previous figure, with a more detailed continuous distribution in black. and shows that the distribution of ambient derates is skewed even when capacities are not truncated.

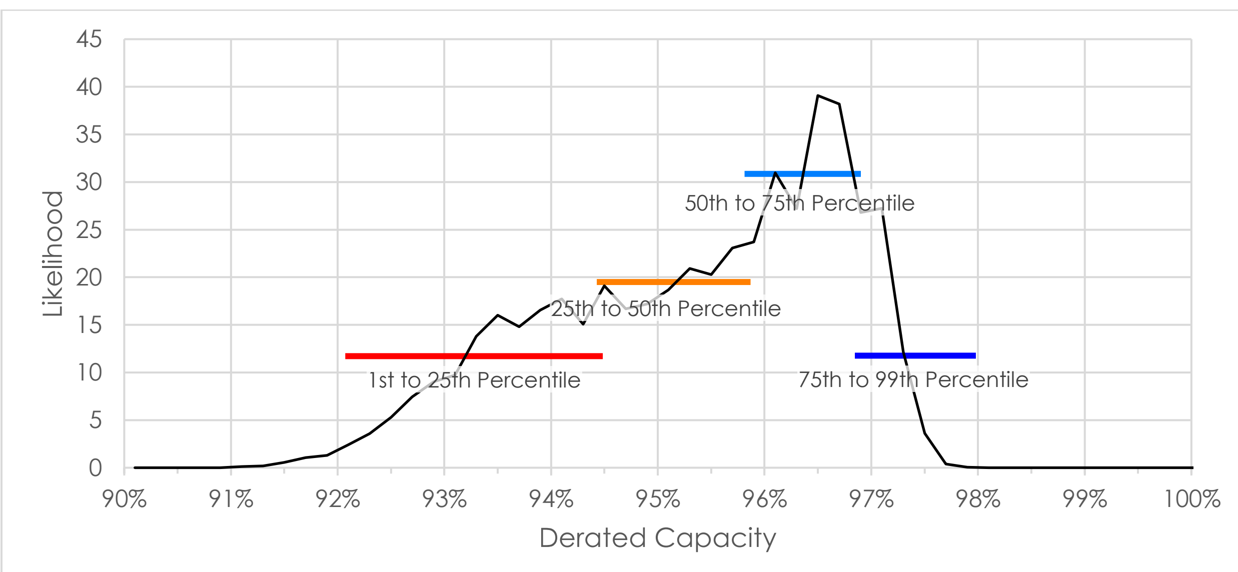

Figure 2 – Modeled Derate Distribution for Combustion Turbines near Sacramento in Months of August in Historic Weather Years 1997-2020

3. Approach

Thermal Powerplant Ambient Derate

Staff conducted a literature review focusing on articles and books investigating the relationship between ambient temperature and output power of natural gas and steam turbines. We analyzed results from several published experiments which ultimately informed the proposed model. The qualitative and quantitative findings from this review supports a general model for derating thermal powerplants inverse linear function of ambient temperature, i.e., available capacity decreases as ambient temperature increases. Reflecting the methods by which thermal powerplants are rated in California, we further propose to limit the model to between 0% and 100% rated capacity, resulting in a piecewise-linear model. Details of the proposed model are presented in Section IV.

Defining Resource Classes

While the general derate approach could be applied to individual generating units, practical constraints such as the limited availability of weather data collocated with generators and observations of similarities among resources suggest that grouped applications are appropriate. For this reason, we propose defining classes of resources based on the type of generator and the location of the resource.

The currently proposed model will apply to generators of two unit types—Combustion Turbine and Combined Cycle—near any of 55 known weather stations, resulting in 110 distinct classes available for use in derate forecasting.

Historic Curtailment Calibration

Having established the general properties of a model according to published scientific research on turbine-driven physical processes, the ERM team proceeded to calibrate the model for California's generators by adjusting the model parameters according to historic derating data. This data is published by CAISO as prior-trade curtailments available through their public website (California Independent System Operator 2021). The curtailment reports indicate the affected generation unit, the size of the curtailment in MW, the dates and times curtailments are applied, and the reason for the curtailment, allowing us to match historic curtailments due to temperature with historic weather and assess whether and to what degree the two are correlated. The results for individual curtailed generators were aggregated by unit type to determine appropriate derate model parameters for each resource class. The parameters consist of a slope and a rated temperature below which the forecast capacity is defined to be 100%. The procedure for determining these parameters is discussed in Section III Curtailment Evaluation and Model Calibration.

Integration with Synthetic Weather Cases

Current-climate ambient temperatures are consistent with past historical conditions which have resulted in relatively small derates to effective generator capacities. We therefore do not consider ambient temperature derating in our current modeling methodologies. Our forecasting efforts typically look out 10 years into the future during which time we expect changes to ambient temperatures to be significant enough to have greater impacts on generator effective capacities. CPUC staff are testing this hypothesis by developing synthetic future climates scenarios under a range of future Global Warming Level for use with SERVM. Global Warming Level is defined as the difference in current global atmospheric temperatures relative to preindustrial global temperatures. The approach for developing these synthetic climates start with the existing 23 weather years of hourly temperatures used in the current SERVM model (1997-2020 weather years), and then modifying, or perturbing, the existing historical profiles by a factor reflecting changes in hourly temperatures due to climate change. Climate change information comes from the Coupled Model Intercomparison Project version 6 (CMIP6) data repository. This approach leverages an existing hourly historical weather dataset that is currently being used within both the Integrated Resource Planning and Resource Adequacy proceedings at the CPUC. Details of this approach are covered in a separate paper (CPUC Staff 2022).

While staff continue developing climate-informed synthetic weather cases, we propose to use the ambient derate model with the historic weather data currently used with other SERVM inputs. We anticipate applying the model to the synthetic weather cases in future modeling later this planning cycle.

4. SERVM Production Cost Model

The SERVM model is a stochastic production cost model, relying on hourly dispatch and resource information to determine a Loss of Load Expectation (LOLE) over a given distribution of uncertainty (weather, generator performance, etc.). The proposed ambient derate model will be applied to several power plant classes assigned according to technology and location, based on the proportions of their rated gas turbine and steam turbine capacities and the temperatures at which they are rated. It will be implemented as a script with input parameters for power plant capacities attributed proportionally to the gas and steam turbines representative of the class. Other parameters of the script include minimum cut-off temperature and the hourly forecast ambient temperatures, with outputs averaged across the power plants in each class weighted by total capacity. The script will output hourly profiles of derated capacity expected to be available at each hour in a format compatible with SERVM, which will be loaded into SERVM similar to existing weather profile functionality.

5. Results

Throughout the relevant literature, we noted a common finding that thermal power plant power capacity is inversely and linearly related to ambient temperature, though the extent to which temperature influences power capacity is dependent upon several variables including the configuration of the plant, i.e., which kinds of turbines are used. Our proposed model takes this into account, yielding power capacity as a function of ambient temperature in degrees Celsius, gas turbine capacity in MW, and steam capacity in MW. Additionally, in accordance with how thermal power plants are tested for rated capacity in California, we impose a maximum capacity of 100% for ambient temperatures below that at which the rating test was performed, as well as a minimum capacity of 0%. The resulting model therefore produces a piecewise-linear function of ambient temperature for each power plant configuration.

II. Literature Review

1. Articles

We first reviewed several papers addressing experiments regarding improvements to thermal power plants, especially for use in hot weather environments. Mohanty and Venkatesh propose a novel intake air cooling and heat recovery system which would drop the inlet air temperature to improve the performance of the gas turbine (B. Mohanty 1995). Notably, this paper presents a set of typical gas turbine parameters, including power output, as functions of ambient temperature—the power plant in question has an ISO rating of 100MW at 15°C, and decreases 688.78 kW for each increase of one degree Celsius. Elsewhere, the paper explains "a rise in the ambient temperature by 1°C results in 1% drop from the gas turbine rated capacity." While the intake air cooler design and analysis is not applicable to the current project, the background information and data provide a good baseline for a range of parameters for a potential ambient temperature derating model. Farouk et al. present data collected over a period of two years from a 74MW combined cycle power plant, including temperature and thermal efficiency (Naeim Farouk January 2013). While this paper provides both average input and output energy for each month, the plant was not operating at its peak, and the data do not lend themselves to calculating the effect of ambient temperature on maximum capacity in particular.

Other papers investigate various thermodynamic behaviors of thermal power plants in detail, albeit for different purposes. Glazer et al. models each process in a combined cycle power plant and runs the model in a simulation using NIST-Refprop 9.0 software (V. Glazar July 2019). The simulation allows the authors to evaluate the capacity and efficiency of the power plant for a wide variety of environmental conditions. Similarly, Lee et al. develop a model that combines thermodynamic process simulation and statistical prediction (Jae Hong Lee February 6, 2017). As an input to their model, Lee et al. apply a power correction factor curve which is linear in the shown temperature range of -10 °C and 40°C. Mohanty and Venkatesh build up a detailed model from first principles, detailing each of the thermodynamic formulas used in simulating the physical processes in and around each turbine, and developing their own MATLAB script to simulate a theoretical power plant (Dillip Kumar Mohanty August, 2014). Their code is unavailable and would require a MATLAB license in order to execute. While these papers provide limited datasets from their experiments and their approaches look promising, the anticipated time and effort required to run similar simulations for an array of power plants in order to generate the correction factor curves suited for our purposes is beyond the scope of this project.

The Department of Energy's handbook on gas turbine and combined cycle powerplants contains a wealth of qualitative information regarding the design and function of these power plants, as well as the history of gas turbines both in stationary and aerospace applications (Soares 2006). The Handbook also outlines many characteristics of thermal power generation, including a negative correlation between ambient temperature and power output. While confirming patterns we observe elsewhere in literature regarding the effects of ambient temperatures on thermal power capacity, the Handbook emphasizes gas turbine operation and properties without providing similar detail regarding the steam processes in combined cycle power generation, and generally lacks quantitative information that could be incorporated into an ambient derating model.

Finally, Şen et al. take an empirical approach to assessing the impact of elevated ambient temperatures on combined cycle power plants (Günnur Şen November 5, 2018). This paper presents a case study of a combined cycle power plant and provides the power output of each turbine—four gas turbines feeding into two steam turbines—across a range of temperatures between 8°C and 23°C, which allows for analysis at varying levels of granularity—i.e., individual turbines, gas or steam turbines only, either of the two blocks of two gas turbines and one steam turbine, or full facility. We perform linear regression analyses on the data from this paper to determine curve parameters applicable to our proposed derate model.

2. Summary of Findings

Combined cycle powerplants consist of one or more gas turbo-compressors operating in a Joule-Brayton thermodynamic cycle paired with a typically smaller number of steam turbines operating in a Rankine cycle (Dillip Kumar Mohanty August, 2014). These plants often are designed with of multiple modular "blocks" of gas and steam turbines arranged, which provide benefits in construction and allow greater operational flexibility and efficiency when ramping power output up or down (Soares 2006). Across many of the articles we reviewed, a consensus emerged that there is an inversely proportional relationship between ambient temperature and power capacity, though the slope of the correlation varies among cases. In Şen et al., it is evident that the gas and steam turbines react to ambient temperature changes. The results of our linear regression of various aggregated generation components are presented in Table 1, and show that, while the two blocks—each consisting of two gas turbines and one steam turbine—behave very similarly to each other, there is a significant difference between the slopes of the best-fit lines between the gas- and steam-powered generators. These coefficients correspond to an equation of the form $y = \beta_0 x_0 + \beta_1 x_1$ where $x_0 = 1$ and $x_1 = T_{amb}$.

Table 1 – Linear Regression Coefficients for Combined Cycle Power Capacity vs. Temperature

Coefficient	% Total Capacity Block 1	% Total Capacity Block 2	% Total GT Capacity	% Total ST Capacity	% Total Cap.
β_0:	114.14%	113.95%	113.76%	115.27%	114.05%
β_1:	-0.96%	-0.97%	-0.94%	-1.05%	-0.96%

These results demonstrate that the power capacity of a steam turbine is more readily influenced by the ambient temperature than a gas turbine. These results align with intuition, given the broader range of temperatures across which the gas turbine's Joule-Brayton cycle operates vs. the steam engine's Rankine cycle—flue gasses from a gas turbine are typically several hundred degrees higher than the inlet temperatures for a steam turbine (A. Ganjehkaviri March 22, 2014). Figure 3, provided by Mohanty and Venkatesh, shows both cycles in a single temperature-entropy diagram. In this type of diagram, the area surrounded by a cycle is equal to its theoretical work output. Increasing the ambient temperature effectively raises the lowest points of both cycles, reducing each cycle's rate of work output. Since the Rankine cycle has a lower maximum temperature versus the Brayton cycle, and includes an isothermal process which occurs at its minimum temperature, the two types of turbines are likely to respond differently to changes in ambient temperatures.

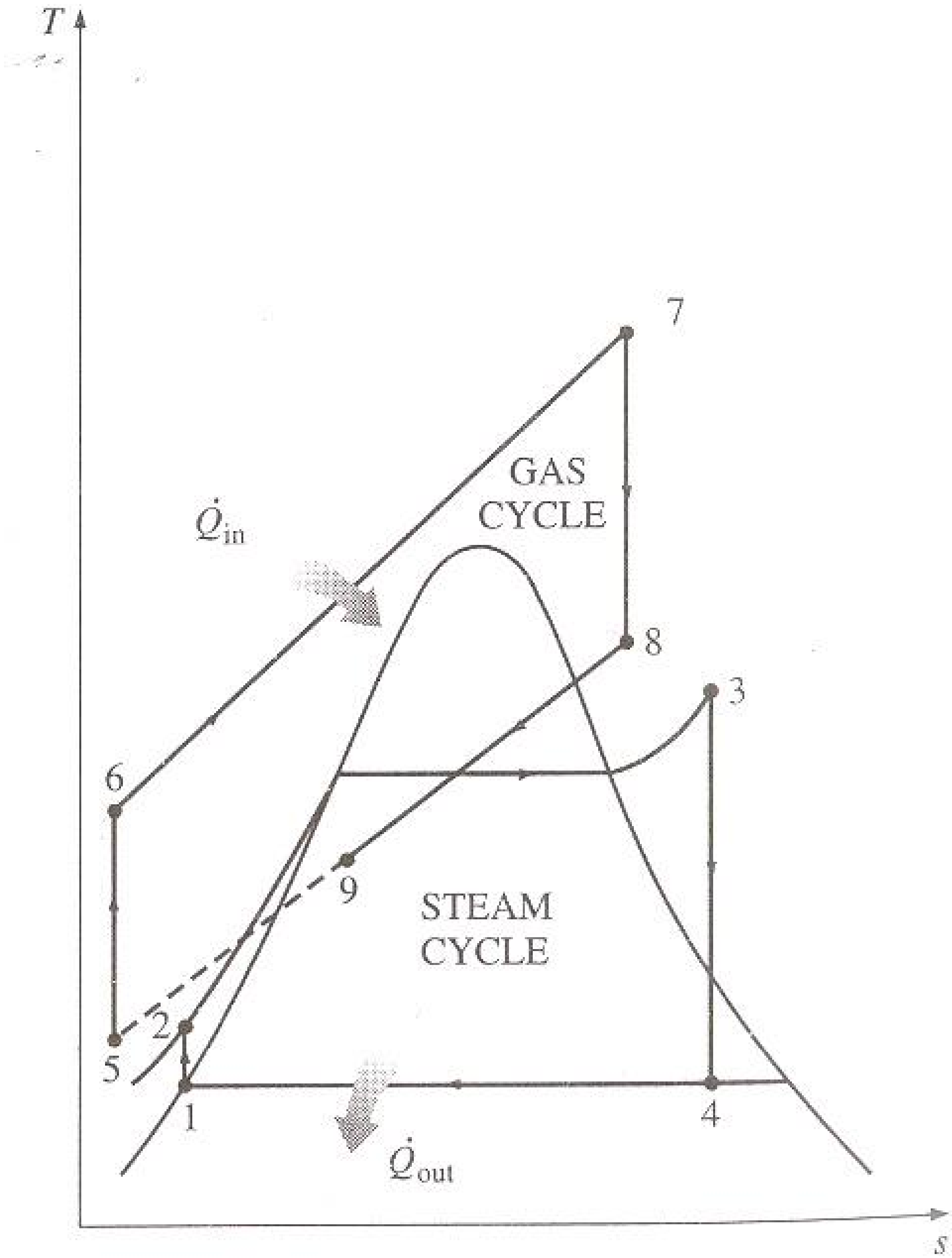

Figure 3 – Temperature-Entropy Diagram of a Combined Joule-Brayton (Gas) and Rankine (Steam) Cycle Power Plant

III. Curtailment Evaluation and Model Calibration

To evaluate the findings that inform the proposed model against real-world data, we analyzed a set of derate events due to ambient temperatures from CAISO's prior trade day curtailment report (California Independent System Operator 2021). At time of writing, these reports are publicly available via CAISO's website from June 18, 2021, through the prior day. CPUC maintains an internal database with geospatial data for the generation resources included in CAISO's report, which allows us to match each with a weather station. We then combine historical hourly weather data for each weather station and hourly generator curtailments, and thereby determine best-fit regression curves to describe the relationships between ambient dry- and wet-bulb temperatures and percent curtailment, and to compare the results against the proposed model.

1. Procedure

Staff performed the following tasks in evaluating curtailments due to ambient temperature:

1. Identify appropriate weather stations for each generator resource listed in Forced_AmbientTemp.csv
    a. ERM team developed a database of weather data from a set of weather stations identified in the table named "latlonmap".
    b. Prepare a Python/psycopg2/postgresql script to determine distances between generation resources and weather stations and identify the closest pairs.
    c. Run script and verify outputs.
2. Obtain contemporary weather data for curtailments.
    a. The ERM weather database on EZDB does not include the days for which CAISO has published prior trade day curtailments, so the data for the identified weather stations must be obtained from NOAA at www.ncei.noaa.gov/access/search/dataset-search
    b. Generate a table of place names for each weather station id paired with resources in the previous step, saved to WeatherStationIDsToNames.csv
    c. Search for the relevant data files on the NOAA website using the place names and select them for download.
    d. Downloading files requires a NOAA account and takes a few minutes to process. The link to download is delivered to the email address associated with the NOAA account.
    e. Download weather data files.
3. Calculate wet-bulb temperatures.
    a. Parse the weather data to extract hourly dry-bulb temperatures, dew points, and atmospheric pressures.
    b. Temperatures (including dry-bulb and dew point) are stored as strings containing the observed temperature in degrees C multiplied by ten, followed by a comma and a single-digit observation quality code. The temperatures must be extracted from the string and converted into floating point numbers, using only observations of sufficient quality.
    c. Atmospheric pressures are stored in the MA1 field as strings containing four comma-separated values: an altimeter setting pressure, an altimeter quality code, an absolute pressure observation, and a pressure quality code. The absolute pressures must be extracted from the string and converted into floating point numbers, using only observations of sufficient quality.

   d. Calculate wet-bulb temperatures using the metpy library's iterative solver with the parsed temperature and pressure values.
   e. Prepare a Python script to perform these operations.
   f. Run the script and verify outputs.
4. Merge the curtailment and weather data on hourly intervals and correlate ambient air temperatures with curtailment amount; and calculate linear regression coefficients.
   a. The curtailment data is presented in inconsistent intervals, and must be normalized in order to compare against weather data
   b. Use the mapping between generation resources and weather stations from step 3 as intermediary between the data sets.
   c. Filter out very high curtailments greater than 30% which are unlikely to be solely attributable to ambient temperature and are considered outside the scope of this modelling effort.
   d. Calculate linear regression coefficients β_0 and β_1, and goodness-of-fit measures, R-Squared, for each resource individually to find the best-fit function for predicted curtailment, $\hat{C}$, as a function of temperature, T, as shown in Equation 1 below.

$$\min_{\beta_0,\beta_1 \in \mathbb{R}} \left(\sum_{i=0}^{N} \left(C_i - \hat{C}(T_i; \beta_0, \beta_1) \right)^2 \right)$$
$$\text{where } \hat{C} = \beta_0 T_i + \beta_1$$

Equation 1 – Curtailment as function of Temperature

   such that the squared residuals (i.e., the difference between observed and predicted curtailments) are minimized across N observations:
   Prepare a Python script to perform these operations.
   e. Run the script and verify outputs.
5. Apply resource-level regression coefficients to normalize temperatures.
   a. Set a target curtailment rate between 0 and the maximum curtailment of 30% as set in the previous filtering step.
   b. Calculate the temperature adjustment factor, ΔT, according to Equation 2 based on a target curtailment C^*, the resource-level regression slope β_0, and the regression intercept value, β_1. Add the result to the observed temperature, T_0.

$$\Delta T = T_0 + \frac{(\beta_1 - C^*)}{\beta_0}$$

Equation 2 – Temperature Normalization

6. Filter out poorly fit resources and perform linear regression on all resources of a given unit type.

a. Use normalized temperatures (either dry- or wet-bulb) to align the curtailment datasets for each resource.
b. Evaluate the linear regression coefficients and goodness-of-fit parameters for each unit-type.
c. Adjusting the target curtailment in the previous step changes how well the resources line-up. Evaluate the linear regressions with various target curtailments to find the target curtailment with yields the best fit for each unit type.

2. Limitations

The weather stations selected for this exercise are pulled from a relatively small set used in the climate forecasting model. This means that some weather stations are up to 180 km from generator resources to which they are paired. For this reason, we will focus our attention on resources with the nearest weather stations. Since the proposed model is expected to use similarly sparse weather stations, this analysis may help inform that design decision.

Additionally, the number of observations for each resource is dependent upon how consistently curtailments are reported to CAISO, both in terms of frequency of reporting and accuracy in attribution. Forced curtailments due to ambient temperature may involve circumstances external to the physical processes addressed in the proposed model. We thus further narrow our attention to resources with higher numbers of reported hours of curtailment. Finally, this analysis ignores non-curtailed hours (i.e., curtailment of 0 MW. This omission is consistent with the proposed model, which assumes constant capacity for temperatures below a threshold, thus we are limiting the scope of this exercise to the non-zero curtailment regime.

3. Results

The curtailments reported to CAISO are subtractive, meaning the listed MW are a reduction from each resource’s capacity. This is inverse from the proposed model, which applies a derate factor to be multiplied by the specified capacity to determine available capacity.

The map in Figure 4 depicts the locations of each of the curtailed generation resources and weather stations, indicated by squares and triangles, respectively.

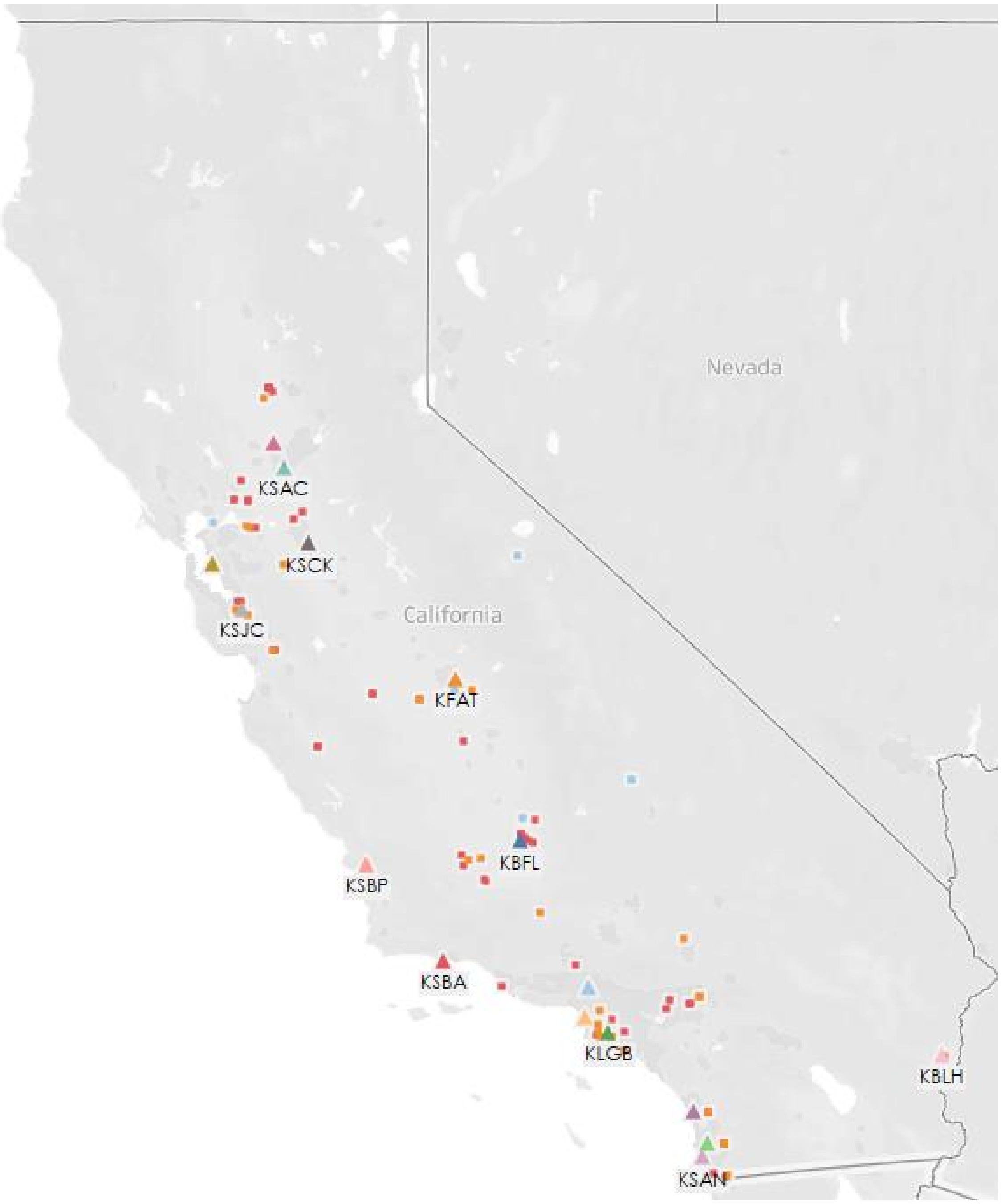

Figure 4 – Locations of Curtailed Thermal Generation Resources (Squares) and Weather Stations (Triangles)

Table 2 summarizes a regression analysis of curtailed resources with at least 300 hours of curtailments between June 18, 2021, and September 19, 2022. The regression coefficient representing the slope of the best fit line evaluated through least-squares regression analysis, and the R-squared term indicating goodness of fit. The maximum R-squared value of 1.0 would indicate that the predicted curtailments perfectly match the observed, while 0.0 would indicates temperature has no predictive value in calculating curtailment).

Table 2 – Curtailment Regression Results by Generation Resource

Resource ID	Unit Type	Number of Observations	Dry-Bulb Slope	Dry-Bulb Intercept	Dry-Bulb R^2	Wet-Bulb Slope	Wet-Bulb Intercept	Wet-Bulb R^2
AGRICO_7_UNIT	COMBINED CYCLE	1,568	0.09%	5.38%	0.021	0.35%	1.81%	0.058
ALAMIT_2_PL1X3	COMBINED CYCLE	3,442	0.06%	-0.26%	0.165	0.16%	-1.59%	0.272
ARCOGN_2_UNITS	COMBINED CYCLE	75	0.10%	1.57%	0.203	0.10%	2.18%	0.083
DELTA_2_PL1X4	COMBINED CYCLE	8,115	0.19%	0.58%	0.167	0.39%	-1.37%	0.328
DUANE_1_PL1X3	COMBINED CYCLE	148	-0.02%	7.66%	0.003	0.00%	7.22%	0.000
ELKHIL_2_PL1X3	COMBINED CYCLE	10,105	0.16%	2.77%	0.384	0.32%	2.02%	0.419
ELSEGN_2_UN1011	COMBINED CYCLE	7,441	0.03%	-0.35%	0.036	0.03%	-0.32%	0.036
ELSEGN_2_UN2021	COMBINED CYCLE	496	-0.04%	1.54%	0.042	-0.13%	2.93%	0.117
GILROY_1_UNIT	COMBINED CYCLE	9,154	0.02%	9.26%	0.003	0.06%	8.82%	0.013
HARBGN_7_UNITS	COMBINED CYCLE	129	-0.13%	24.78%	0.009	-0.02%	21.79%	0.000
HIDSRT_2_UNITS	COMBINED CYCLE	9,641	0.15%	2.10%	0.180	0.32%	0.66%	0.384
HNTGBH_2_PL1X3	COMBINED CYCLE	3,777	0.06%	-0.36%	0.113	0.14%	-1.58%	0.212
LAPLMA_2_UNIT 1	COMBINED CYCLE	10,353	0.09%	2.57%	0.111	0.13%	2.30%	0.157
LAPLMA_2_UNIT 2	COMBINED CYCLE	9,191	-0.10%	9.34%	0.069	-0.04%	8.11%	0.007
LAPLMA_2_UNIT 3	COMBINED CYCLE	10,259	0.03%	3.73%	0.020	0.03%	3.73%	0.021
LAPLMA_2_UNIT 4	COMBINED CYCLE	10,422	-0.03%	9.35%	0.011	0.03%	8.38%	0.005
LAROA2_2_UNITA1	COMBINED CYCLE	6,529	0.19%	1.13%	0.229	0.34%	-0.56%	0.354
LEBECS_2_UNITS	COMBINED CYCLE	6,878	0.05%	0.81%	0.101	0.11%	0.35%	0.125
LGHTHP_6_ICEGEN	COMBINED CYCLE	54	-0.35%	18.28%	0.674	-0.85%	26.09%	0.549
LMEC_1_PL1X3	COMBINED CYCLE	10,156	0.01%	3.20%	0.001	0.03%	3.01%	0.003
MAGNLA_6_ANAHEIM	COMBINED CYCLE	956	0.16%	0.08%	0.177	0.39%	-3.41%	0.239
METEC_2_PL1X3	COMBINED CYCLE	8,269	0.09%	1.16%	0.090	0.21%	0.03%	0.157
MOSSLD_2_PSP1	COMBINED CYCLE	780	-0.01%	1.89%	0.001	-0.02%	2.03%	0.006
MOSSLD_2_PSP2	COMBINED CYCLE	735	0.01%	1.40%	0.003	0.02%	1.33%	0.004
MRCHNT_2_PL1X3	COMBINED CYCLE	9,048	0.44%	0.82%	0.258	0.68%	-0.81%	0.406
NGILAA_5_SDGDYN	COMBINED CYCLE	11,992	0.30%	1.21%	0.385	0.48%	0.01%	0.657
OTMESA_2_PL1X3	COMBINED CYCLE	10,130	0.32%	-1.78%	0.445	0.40%	-1.82%	0.543
PALOMR_2_PL1X3	COMBINED CYCLE	4	0.00%	5.22%	0.000	0.00%	5.22%	0.000
SBERDO_2_PSP3	COMBINED CYCLE	6,123	0.10%	0.43%	0.088	0.26%	-1.71%	0.201
SBERDO_2_PSP4	COMBINED CYCLE	6,831	0.14%	0.05%	0.148	0.30%	-1.85%	0.279
SCHLTE_1_PL1X3	COMBINED CYCLE	9,041	0.16%	2.83%	0.350	0.34%	1.56%	0.462
SGREGY_6_SANGER	COMBINED CYCLE	15	0.00%	6.83%	1.000	0.00%	6.83%	1.000
SUNRIS_2_PL1X3	COMBINED CYCLE	11,227	0.11%	4.68%	0.469	0.22%	4.26%	0.483
SUTTER_2_CISO	COMBINED CYCLE	5,770	0.15%	0.83%	0.124	0.36%	-0.98%	0.132

Resource ID	Unit Type	Number of Observations	Dry-Bulb Slope	Dry-Bulb Intercept	Dry-Bulb R^2	Wet-Bulb Slope	Wet-Bulb Intercept	Wet-Bulb R^2
TERMEX_2_PL1X3	COMBINED CYCLE	6,814	0.12%	0.94%	0.199	0.22%	-0.33%	0.355
VERNON_6_MALBRG	COMBINED CYCLE	8	0.00%	2.16%	1.000	0.00%	2.16%	1.000
AGRICO_6_PL3N5	COMBUSTION TURBINE	1,883	-0.09%	11.28%	0.010	-0.03%	8.99%	0.000
ALMEGT_1_UNIT 1	COMBUSTION TURBINE	8,908	0.18%	7.53%	0.084	0.19%	8.09%	0.066
ALMEGT_1_UNIT 2	COMBUSTION TURBINE	9,666	0.19%	5.75%	0.083	0.23%	5.99%	0.079
BARRE_6_PEAKER	COMBUSTION TURBINE	4,062	0.39%	-0.87%	0.240	0.84%	-6.47%	0.438
BASICE_2_UNITS	COMBUSTION TURBINE	5,038	-0.01%	2.62%	0.001	-0.03%	2.92%	0.003
BDGRCK_1_UNITS	COMBUSTION TURBINE	10,393	0.00%	7.94%	0.000	0.01%	7.83%	0.000
BEARMT_1_UNIT	COMBUSTION TURBINE	10,403	0.18%	2.76%	0.510	0.36%	2.09%	0.490
BOGUE_1_UNITA1	COMBUSTION TURBINE	2,087	0.11%	1.14%	0.157	0.33%	-1.41%	0.196
BORDER_6_UNITA1	COMBUSTION TURBINE	91	0.00%	13.68%	0.000	0.09%	11.77%	0.022
CALPIN_1_AGNEW	COMBUSTION TURBINE	1,681	0.05%	1.27%	0.105	0.06%	1.28%	0.055
CARLS2_1_CARCT1	COMBUSTION TURBINE	3,656	0.08%	1.01%	0.027	0.16%	-0.12%	0.049
CENTER_6_PEAKER	COMBUSTION TURBINE	2,773	-0.05%	5.55%	0.009	-0.07%	5.59%	0.004
CENTRY_6_PL1X4	COMBUSTION TURBINE	324	-0.04%	10.06%	0.005	-0.33%	15.64%	0.089
CHALK_1_UNIT	COMBUSTION TURBINE	10,498	0.03%	7.24%	0.026	0.06%	7.12%	0.025
COCOPP_2_CTG1	COMBUSTION TURBINE	8,686	0.18%	0.10%	0.290	0.28%	-0.77%	0.434
COCOPP_2_CTG2	COMBUSTION TURBINE	8,413	0.17%	0.02%	0.272	0.27%	-0.83%	0.414
COCOPP_2_CTG3	COMBUSTION TURBINE	9,792	0.25%	1.32%	0.394	0.36%	0.60%	0.540
COCOPP_2_CTG4	COMBUSTION TURBINE	8,394	0.19%	-0.09%	0.297	0.31%	-1.13%	0.473
CSCGNR_1_UNIT 1	COMBUSTION TURBINE	10	-0.20%	12.94%	0.472	-0.59%	18.12%	0.549
CSCGNR_1_UNIT 2	COMBUSTION TURBINE	30	0.00%	7.07%	0.000	0.00%	7.07%	0.000
DOUBLC_1_UNITS	COMBUSTION TURBINE	10,600	0.12%	0.75%	0.619	0.24%	0.30%	0.603
DREWS_6_PL1X4	COMBUSTION TURBINE	282	0.03%	11.94%	0.006	0.11%	10.60%	0.016
ESCNDO_6_PL1X2	COMBUSTION TURBINE	1,343	0.05%	3.03%	0.026	0.11%	1.91%	0.050
ESCNDO_6_UNITB1	COMBUSTION TURBINE	86	0.00%	8.39%	1.000	0.00%	8.39%	1.000
ETIWND_6_GRPLND	COMBUSTION TURBINE	3,232	-0.07%	6.09%	0.015	-0.09%	6.06%	0.005
GILRPP_1_PL1X2	COMBUSTION TURBINE	42	0.04%	2.63%	0.209	0.11%	1.86%	0.254
GILRPP_1_PL3X4	COMBUSTION TURBINE	23	0.00%	2.60%	1.000	0.00%	2.60%	1.000
GRNLF2_1_UNIT	COMBUSTION TURBINE	524	-0.02%	5.00%	0.006	-0.07%	5.60%	0.008
GWFPWR_1_UNITS	COMBUSTION TURBINE	10,369	0.24%	-0.43%	0.508	0.52%	-2.26%	0.602
HINSON_6_LBECH2	COMBUSTION TURBINE	10	0.00%	11.11%	0.000	0.00%	11.11%	0.000
INDIGO_1_UNIT 1	COMBUSTION TURBINE	311	0.25%	0.94%	0.296	0.62%	-4.13%	0.644
INDIGO_1_UNIT 2	COMBUSTION TURBINE	306	0.27%	3.33%	0.204	0.66%	-2.00%	0.500
INDIGO_1_UNIT 3	COMBUSTION TURBINE	346	0.25%	4.84%	0.181	0.64%	-0.47%	0.426

Resource ID	Unit Type	Number of Observations	Dry-Bulb Slope	Dry-Bulb Intercept	Dry-Bulb R^2	Wet-Bulb Slope	Wet-Bulb Intercept	Wet-Bulb R^2
KERNFT_1_UNITS	COMBUSTION TURBINE	10,557	0.14%	0.93%	0.533	0.29%	0.27%	0.542
KNGCTY_6_UNITA1	COMBUSTION TURBINE	5,794	0.07%	2.11%	0.047	0.13%	1.57%	0.072
LARKSP_6_UNIT 1	COMBUSTION TURBINE	347	0.03%	3.89%	0.070	0.07%	3.37%	0.158
LARKSP_6_UNIT 2	COMBUSTION TURBINE	376	0.05%	3.13%	0.083	0.14%	1.93%	0.233
LECEF_1_UNITS	COMBUSTION TURBINE	9,924	0.03%	3.21%	0.027	0.04%	3.14%	0.030
LIVOAK_1_UNIT 1	COMBUSTION TURBINE	10,345	0.30%	6.75%	0.547	0.58%	5.78%	0.517
LMBEPK_2_UNITA1	COMBUSTION TURBINE	67	0.03%	2.58%	0.016	0.00%	3.26%	0.000
LMBEPK_2_UNITA2	COMBUSTION TURBINE	185	0.08%	0.41%	0.081	0.27%	-1.73%	0.057
LMBEPK_2_UNITA3	COMBUSTION TURBINE	178	0.06%	0.60%	0.071	0.18%	-0.94%	0.057
LODI25_2_UNIT 1	COMBUSTION TURBINE	12,494	0.20%	7.03%	0.341	0.37%	6.24%	0.347
MIRLOM_6_PEAKER	COMBUSTION TURBINE	3,932	0.23%	-0.01%	0.169	0.55%	-4.14%	0.340
MKTRCK_1_UNIT 1	COMBUSTION TURBINE	8,557	0.02%	6.60%	0.018	0.03%	6.79%	0.005
MNDALY_6_MCGRTH	COMBUSTION TURBINE	3,891	0.33%	4.22%	0.123	0.72%	-0.62%	0.319
OMAR_2_UNIT 4	COMBUSTION TURBINE	9	0.00%	10.67%	1.000	0.00%	10.67%	1.000
OTAY_6_PL1X2	COMBUSTION TURBINE	1	0.00%	24.16%	N/A	0.00%	24.16%	N/A
PIOPIC_2_CTG1	COMBUSTION TURBINE	10,353	0.25%	-0.06%	0.360	0.40%	-1.15%	0.582
PIOPIC_2_CTG2	COMBUSTION TURBINE	10,240	0.24%	-0.96%	0.342	0.39%	-2.07%	0.552
PIOPIC_2_CTG3	COMBUSTION TURBINE	9,143	0.27%	-0.88%	0.302	0.45%	-2.52%	0.506
PNOCHE_1_PL1X2	COMBUSTION TURBINE	3,013	0.00%	5.59%	0.000	0.22%	1.70%	0.021
PNOCHE_1_UNITA1	COMBUSTION TURBINE	69	0.00%	15.38%	0.000	0.00%	15.38%	0.000
RVRVEW_1_UNITA1	COMBUSTION TURBINE	122	0.34%	-2.45%	0.162	0.54%	-3.85%	0.070
SIERRA_1_UNITS	COMBUSTION TURBINE	10,636	0.12%	1.18%	0.591	0.24%	0.70%	0.577
STIGCT_2_LODI	COMBUSTION TURBINE	10,031	0.15%	4.10%	0.216	0.23%	3.94%	0.162
SUNSET_2_UNITS	COMBUSTION TURBINE	8,411	0.16%	-0.33%	0.350	0.34%	-1.32%	0.370
TENGEN_2_PL1X2	COMBUSTION TURBINE	39	0.00%	5.47%	0.000	0.00%	5.47%	0.000
UNVRSY_1_UNIT 1	COMBUSTION TURBINE	4	0.00%	16.05%	1.000	0.00%	16.05%	1.000
VACADX_1_UNITA1	COMBUSTION TURBINE	66	0.00%	13.04%	1.000	0.00%	13.04%	1.000
WALCRK_2_CTG3	COMBUSTION TURBINE	5	-0.60%	26.87%	0.514	-0.85%	25.79%	0.048
WOLFSK_1_UNITA1	COMBUSTION TURBINE	2,076	0.07%	1.31%	0.039	0.17%	0.35%	0.024
YUBACT_1_SUNSWT	COMBUSTION TURBINE	1,035	0.00%	8.64%	0.000	-0.05%	9.32%	0.003
YUBACT_6_UNITA1	COMBUSTION TURBINE	2,455	0.09%	0.92%	0.115	0.21%	-0.15%	0.086
ALAMIT_7_UNIT 3	STEAM	189	0.05%	3.16%	0.003	0.24%	-0.12%	0.011
ALAMIT_7_UNIT 4	STEAM	393	0.12%	2.59%	0.158	0.28%	0.18%	0.133
ALAMIT_7_UNIT 5	STEAM	176	0.08%	3.40%	0.183	0.29%	-0.14%	0.266
CONTRL_1_OXBOW	STEAM	547	0.00%	7.40%	0.001	-0.03%	7.82%	0.007
CROKET_7_UNIT	STEAM	15	-0.68%	32.32%	0.820	-3.39%	78.33%	0.509

Resource ID	Unit Type	Number of Observations	Dry-Bulb Slope	Dry-Bulb Intercept	Dry-Bulb R^2	Wet-Bulb Slope	Wet-Bulb Intercept	Wet-Bulb R^2
HNTGBH_7_UNIT 2	STEAM	261	0.08%	1.76%	0.072	0.48%	-5.80%	0.306
INTMNT_3_ANAHEIM	STEAM	220	0.00%	1.27%	0.000	0.00%	1.27%	0
INTMNT_3_RIVERSIDE	STEAM	121	0.01%	1.35%	0.001	-0.11%	3.37%	0.025
MTNPOS_1_UNIT	STEAM	289	0.05%	14.93%	0.018	0.33%	10.70%	0.108
ORMOND_7_UNIT 1	STEAM	42	0.26%	6.86%	0.023	-0.77%	30.73%	0.015
ORMOND_7_UNIT 2	STEAM	60	0.16%	5.38%	0.101	0.36%	2.28%	0.073
REDOND_7_UNIT 5	STEAM	80	-0.01%	7.78%	0.001	0.07%	6.05%	0.001
REDOND_7_UNIT 6	STEAM	441	0.11%	6.57%	0.047	0.08%	7.77%	0.003
REDOND_7_UNIT 8	STEAM	170	-0.04%	8.92%	0.002	0.49%	-2.43%	0.023
ULTPFR_1_UNIT 1	STEAM	14	0.00%	6.17%	0.000	0.00%	6.17%	0.000

Based on Table 2, wet-bulb temperatures appear to have a slightly stronger predictive relationship with curtailment for many generation resources, though in several cases the dry-bulb temperatures are more predictive. However, because the improvement is neither substantial nor uniform, dry-bulb temperatures are considered sufficient for calibration.

The charts in Figure 5 show the reported hourly curtailments plotted with respect to the historic temperature at the nearest available weather station for all resources (including non-thermal power-plants), and the best fit line. Reported curtailments above 30% are excluded from the regression analysis, as such curtailment events are not of the kind intended to be modeled in this project. These plots demonstrate that many resources, especially among thermal generators, demonstrate a positive, linear correlation between temperature and curtailment. In some cases, there either exists insufficient data or the variables are too poorly correlated to draw conclusions about a relationship between ambient temperature and curtailment.

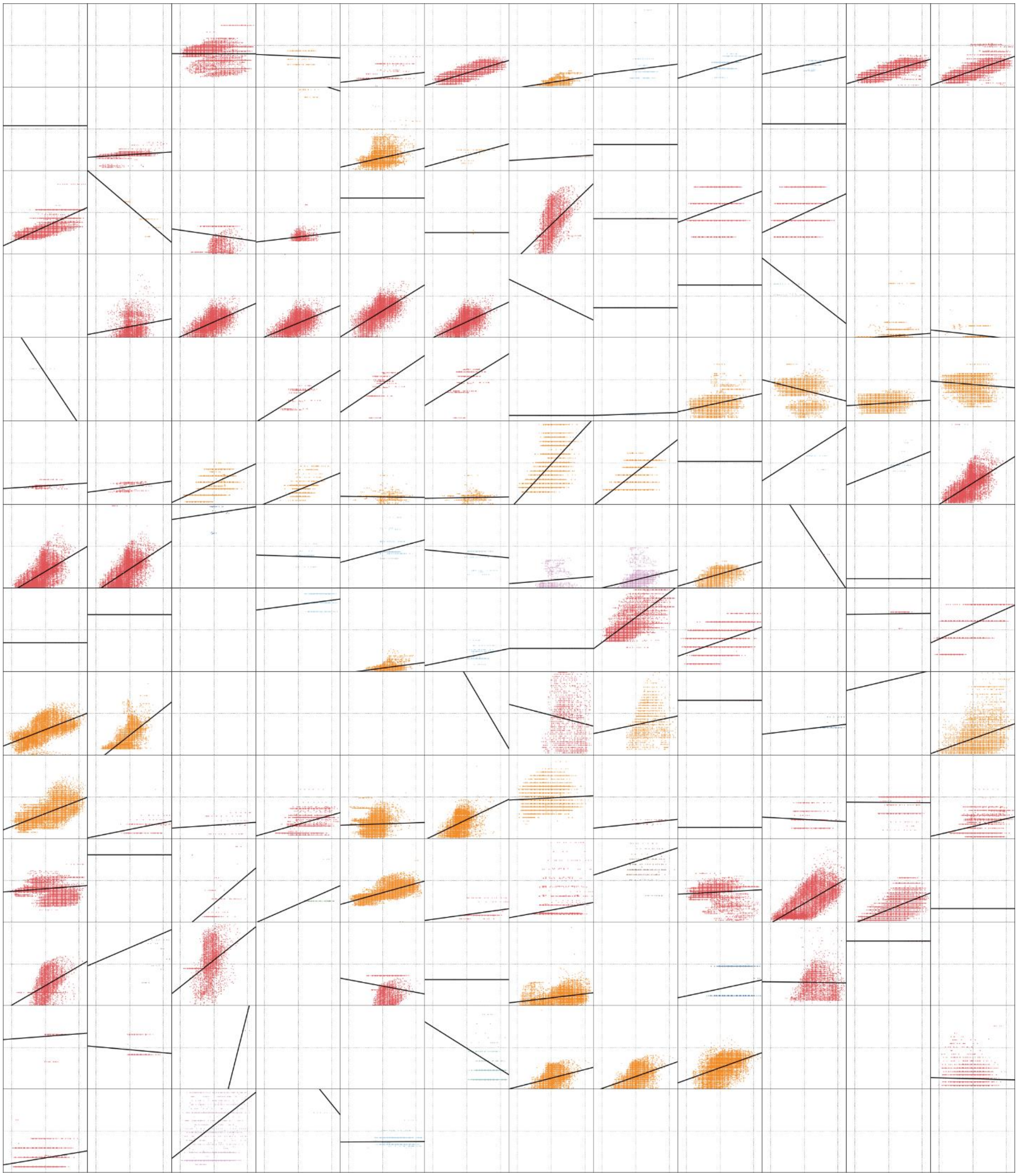

Figure 5 – Best Fit Lines for Curtailment as a function of Dry-Bulb Temperature for All Resources

The regression coefficients β_0 and $\beta_1$calculated for each generation resource (see Equation 1), corresponding to the slope and vertical intercept of the best-fit lines, are used to normalize temperatures according to Equation 2. Adjusting the target temperature, T^*, changes how the data from multiple resources overlap when aggregated to each unit type. An optimal T^* is determined by performing linear regression analyses and calculating the goodness of fit for the normalized data with varying target temperatures. Figure 6 shows that for both dry- and wet-bulb temperatures, combustion turbines and combined cycle generators show best regression performance with a target curtailment between 4% and 6%.

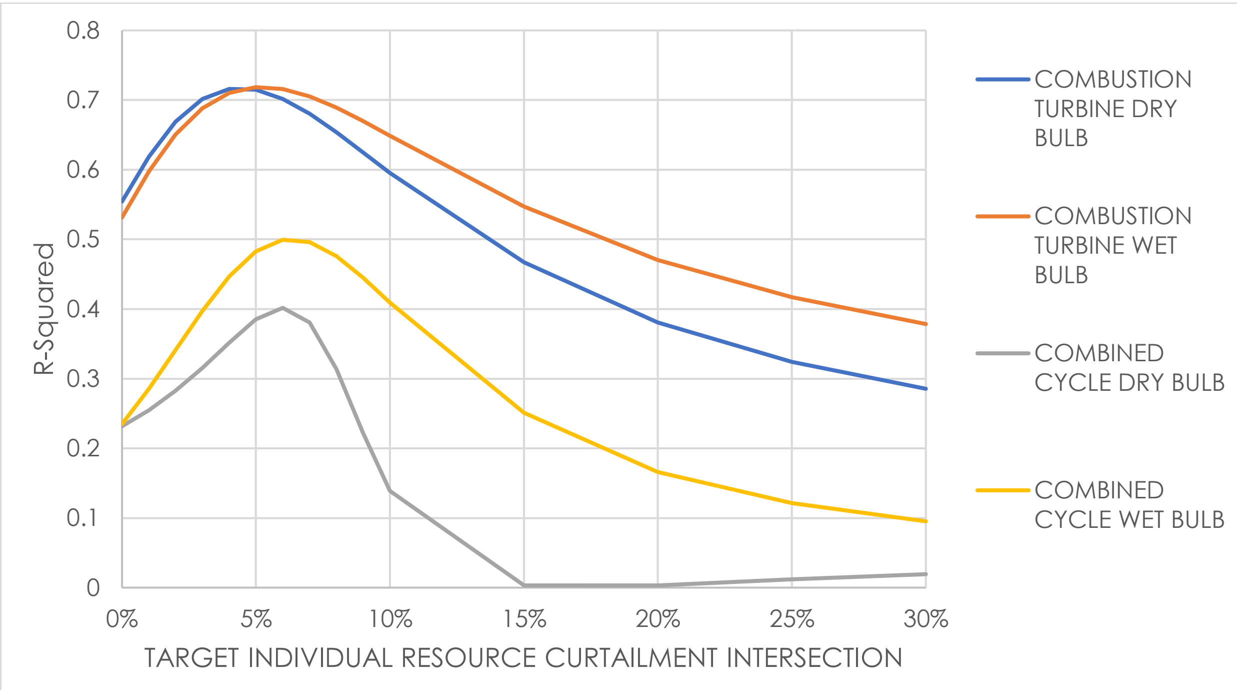

Figure 6 – Unit Type Regression Fitness vs. Target Curtailment Percentage

Applying a target curtailment of 5.5% results in good alignment of combustion turbine curtailments vs. normalized temperatures as shown in Figure 7, which includes all combustion turbine resources with individual R-Squared values greater than 0.35. Note that two resources demonstrate a negative correlation between temperature and curtailment, resulting in a downward-sloping best-fit line, but these resources had very few observations on which to base regression analyses, so their contributions to the best fit by unit-type will be limited.

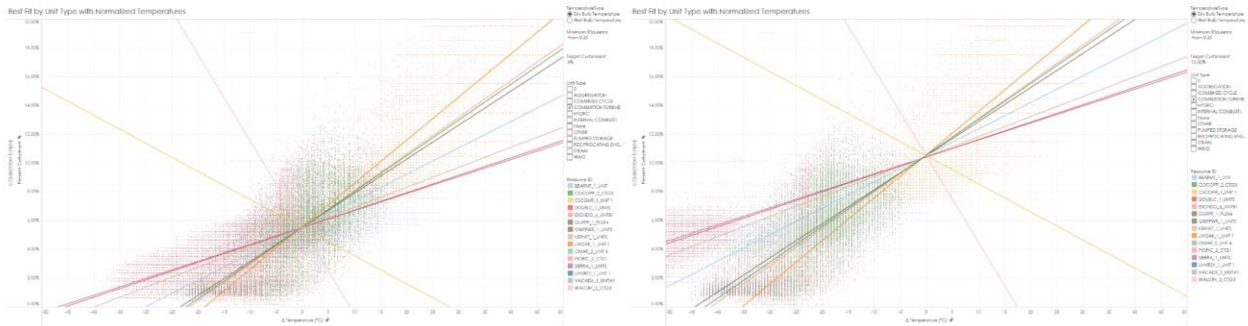

Figure 7 – Best Fit Curves for Multiple Combustion Turbine Resources with Normalized Dry-Bulb Temperatures with target intersections at 5.5% and 10.5% curtailment

Finally, linear regression analyses are performed on the curtailments and normalized temperatures for each unit type to determine regression coefficients for forecasting class-wide curtailments as a function of ambient dry-bulb temperature. The results are shown in Figure 8, and the calibrated model parameters are presented in Table 3.

Figure 8 – Best Fit Curves for Combined Cycle and Combustion Turbine Resources with Normalized Dry-Bulb Temperatures

Table 3 – Calibrated Regression Parameters

Unit Type	Slope	R-Squared
Combined Cycle	0.1650%	0.406
Combustion Turbine	0.2135%	0.719

IV. Proposed Model and Justification

1. Derate Model Definition

Based on our review of the literature presented above, we propose a model which applies a piecewise-linear relationship between ambient temperature and power capacity for any given thermal powerplant. Given the observed differences in how gas turbines respond to varying ambient temperature versus steam turbines, this model accounts for each power plant's tributary power sources. This model will be based on a correction factor which, when applied to a plant's rated power capacity, provides an approximation of capacity available at a given ambient temperature. The correction factor should, therefore, be 100% at the rating temperature of 15°C.

Data from Şen et al. show that, between 8°C and 40°C, gas turbines capacity is attenuated at a rate of -0.94%/°C, and steam turbine capacity is similarly attenuated at approximately -1.05%/°C (Günnur Şen November 5, 2018). For lower temperatures, we note that various configurations of W501F 2x1 combined cycle plants discussed in the Department of Energy's handbook on gas turbine and combined cycle powerplants have correction factors with variable slopes that, at -15°C, are substantially less steep than the slopes above 15°C (Soares 2006). Furthermore, we recognize that power plant capacities in California for resource adequacy planning purposes are determined by testing during the coldest day in February, which tends to occur when the ambient temperature is below the International Standards Organization rating temperature of 15°C cited throughout the literature. We therefore propose our model plant to have a maximum capacity of 100% of their tested capacity for temperatures below the test temperature. We also propose a threshold of 0% for high temperatures well above any forecast ambient temperature where the correction factor would otherwise become negative.

Historic curtailment data support the fundamental structure of the proposed model for thermal power plants—i.e., increased temperatures yield lower capacities (increased curtailments), and the relationship appears linear—however, combined cycle and gas turbine powerplants demonstrate significantly reduced sensitivity to temperature than the academic literature would suggest. Various factors may be contributing to the approximately five-fold reduction in temperature-sensitivity, including the incorporation of inlet air cooling devices which are not accounted for in the proposed model. By substituting the regression factors from our analysis of historic curtailment data into the engineering model derived from literature review, we can account for these factors, both known and unknown, and improve the model's predictive power. This assumes that future thermal power plants behave similarly to the observed curtailments in the data set; any new technologies that may alter powerplants' behavior in high temperatures may render this assumption invalid, but this nonetheless improves the forecast.

Applying the regression analysis calibration data, we define a slope constant K, based on the unit type of the generator, P_{GT} and P_{ST}, respectively. Equation 3 provides the constant for combined cycle and gas turbine generators.

$$K = \begin{cases} -0.1650\%/°\text{C} \text{ for combined cycle} \\ -0.2135\%/°\text{C} \text{ for gas turbine} \end{cases}$$

Equation 3—Slope Constant

We use the value of the slope constant K in evaluating the ambient temperature correction factor, CF, for temperatures between the temperature at which the maximum capacity test was conducted, $T_{P_{NDC}}$, and the temperature at which this line would drop below 0% capacity. For temperatures below $T_{P_{NDC}}$ capacity is held constant at 100%, and for high temperatures, capacity is constrained to a minimum of 0%.

$$CF = \begin{cases} 100\% & \left| T_{amb} < T_{P_{NDC}} \right. \\ K \cdot T_{amb} + 100\% - K \cdot T_{P_{NDC}} & \left| T_{P_{NDC}} \le T_{amb} < T_{P_{NDC}} - \frac{100\%}{K} \right. \\ 0\% & \left| T_{P_{max}} - \frac{100\%}{K} \le T_{amb} \right. \end{cases}$$

Equation 4—Correction Factor

Figure 9 below shows an example correction factor curve for a hypothetical combined cycle power plant with rated power generation capacities of 100MW from gas turbine generators and 50MW from steam, tested at 8°C. The chart depicts the piecewise-linear correction factor function defined for three regions in the lower left.

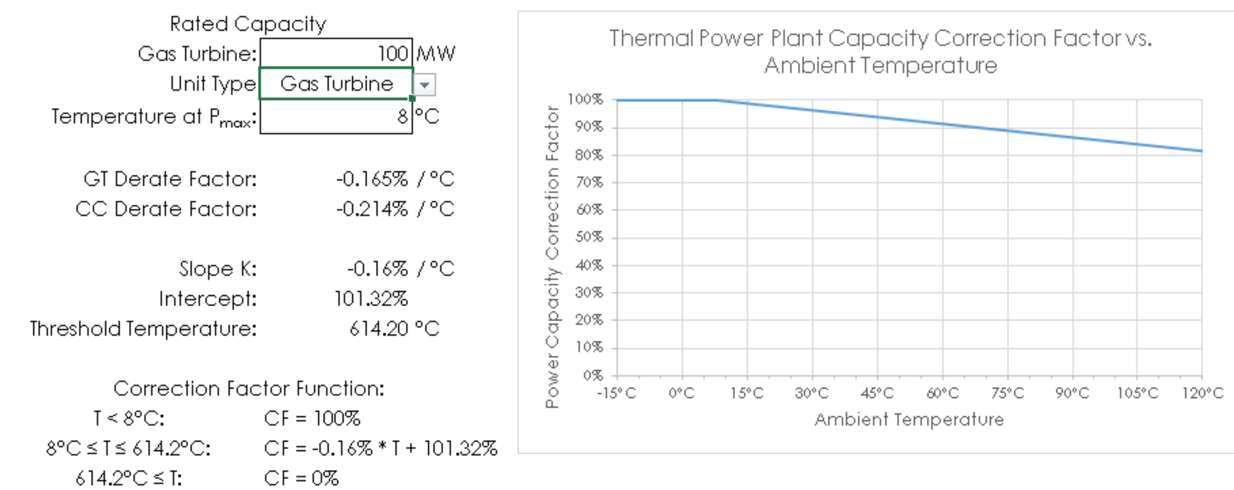

Figure 9—Power Capacity Correction Factor Curve for a Typical Gas Turbine Power Plant

This proposed model will be applied to classes of power plants, consisting of one or more facilities of a given unit type (i.e., gas turbine or combined cycle) within regions of similar weather based on their geographic location. For each class, the P_{max} temperature will be assumed to be the minimum daily-averaged temperature for the associated weather station in the standard weather year. Class-wide derate factors will then be forecast based on climate-informed weather forecasts that incorporates both historical weather and CMIPS6 climate forecasts, and the percent derates will be applied to each resource within the class.

2. Derate Model Justification

The proposed piecewise-linear correction factor model aligns with our findings in the literature about power capacity and provides flexibility to accommodate the variety of powerplants installed and planned throughout the Western United States.

The literature recognizes a linear regime in power capacity vs. ambient temperatures for temperatures above freezing. Few papers, however, address lower temperatures. In California, the rated maximum power capacities of thermal power plants used in resource adequacy planning are determined based on performance tests conducted on a date of the power plant operator's choosing, generally on a cold day in February (California Indenpendent System Operator 2020). Based on this consideration, our model caps the capacity factor at 100%, which means it is constant below the temperature at which capacity test was conducted. This is consistent with historic curtailments which are not reported at or below zero.

The slopes for gas turbine and combined-cycle capacity factors are derived from historic weather and curtailment data. Unfortunately, we have insufficient data to calibrate the model for steam turbine generators at this time.

While a full simulation and a model with many more parameters might more fully account for the diversity of generator configurations, the proposed model is appropriate for use in a long-horizon simulation using weather predictions with relatively high variability and low certainty. It allows for some tailoring based on readily available information without requiring extensive data collection for existing or future power plants.

3. Sample Implementation

The following Python code represents an example implementation of the proposed model. The code defines two functions, named `correction_factor` and `adjusted_capacity`, both with three input parameters representing the ambient temperature, gas turbine rated capacity, and steam turbine rated capacity. The correction factor function provides a normalized value, returning 1.00 at an input ambient temperature of 15 degrees, while the adjusted capacity function multiplies the correction factor by the sum of the input gas and steam rated capacities. This implementation does not account for aggregating power plants into classes.

```
def correction_factor(
  ambient_temperature:float,
  test_temperature:float,
  unit_type:str
) -> float:
  gas_turbine_derate_factor = -0.001650
```

```
  combined_cycle_derate_factor = -0.2135
  if ambient_temperature<test_temperature:
    correction_factor = 1.00
  elif ambient_temperature<test_temperature-1/slope_K:
    if unit_type=='gas_turbine':
      correction_factor = gas_turbine_derate_factor * \
        ambient_temperature + 1 - test_temperature * \
        gas_turbine_derate_factor
    else:
      correction_factor = combined_cycle_derate_factor * \
        ambient_temperature + 1 - test_temperature * \
        combined_cycle_derate_factor
  else:
    correction_factor = 0.00
  return correction_factor

def adjusted_capacity(
  ambient_temperature:float,
  test_temperature:float,
  unit_type:str,
  rated_capacity:float
) -> float:
  cf = correction_factor(
    ambient_temperature,
    test_temperature,
    unit_type
  )
  adjusted_capacity = cf * rated_capacity
  return adjusted_capacity
```

Figure 10—A Simple Implementation of the Proposed Model in Python

The P_{max} test specification does not include recording the ambient temperature at the time of testing, so this data will be collected from historical weather data referenced against the recorded test time and the location of the power plant.

V. Conclusion

The proposed model satisfies this project's stated objectives—it is derived from a broad survey of relevant literature and data and calibrated against reported curtailments and weather, it is simple enough to apply across many generation facilities while allowing tailoring for varying configurations without requiring additional data collection for each site, and it will be a relatively simple matter to implement the model in SERVM. CPUC Staff recommend using the model to forecast derated capacities of combustion turbine and combined cycle power plants in the upcoming R.21-10-002 planning cycle.

VI. References

A. Ganjehkaviri, M.N. Mohd Jaafar, P. Ahmadi, H. Barzegaravval. March 22, 2014. "Modelling and Optimization of Combined Cycle Power Plant Based on Exergoeconomic and Environmental Analysis." *Applied Thermal Engineering 67* 566-578.

Ashley De Sa, Sarim Al Zubaidy. June 12, 2011. "Gas Turbine Performance at Varying Ambient Temperature." *Applied Thermal Engineering.*

B. Mohanty, G. Paloso Jr. 1995. "Enhancing Gas Turbine Performance by Intake Air Cooling using an Absorption Chiller." *Heat Recovery Systems & CHP, Vol. 15, No. 1* 41-50.

California Indenpendent System Operator. 2020. "California ISO Procedure 5330 Version 12: Resource Testing Guidelines." *CAISO.com.* April 16. Accessed July 18, 2022. http://www.caiso.com/Documents/5330.pdf.

California Independent System Operator. 2021. "Curtailed and Non-Operational Generators in California and Neighboring Balancing Authorities." *CAISO.com.* 6 19. Accessed 9 19, 2022. https://www.caiso.com/market/Pages/OutageManagement/CurtailedandNonOperationalGenerators.aspx.

CPUC Staff. 2022. *CPUC Staff Proposal for Development of Synthetic Weather Profiles Reflecting Climate Change.* Staff Proposal, San Francisco: CPUC Energy Division.

Dillip Kumar Mohanty, Vijay Venkatesh. August, 2014. "Performance Analysis of a Combined Cycle Gas Turbine Under Varying Operating Conditions." *Mechanical Engineering: An International Journal, Vol. 1, No. 2.*

Günnur Şen, Mustafa Nil, Hayati Mamur, Halit Doğan, Mustafa Karamolla, Mevlüt Karaçor, Fadıl Kuyucuoğlu, Nuran Yörükeren, Mohammad Ruhul, Amin Bhuiyan. November 5, 2018. "The Effect of Ambient Temperature on Electric Power Generation in Natural Gas Combined Cycle Power Plant--A Case Study." *Energy Reports 4* 682-690.

Jae Hong Lee, Tong Eop Kim, Eui-hwan Kim. February 6, 2017. "Prediction of Power Generation Capacity of a Gas Turbine Combined Cycle Cogeneration Plant." *Energy.*

Naeim Farouk, Lieu Sheng, Quaisar Hayat. January 2013. "Effect of Ambient Temperature on the Performance of Gas Turbines Power Plant." *International Journal of Computer Science, Vol. 10, Issue 1, No. 3.*

National Oceanic and Atmospheric Administration. n.d. "Integrated Surface Dataset." *Data Search | National Centers for Enviornmental Information (NCEI).* Accessed 11 8, 2022. https://www.ncei.noaa.gov/access/search/data-search/global-hourly.

Soares, Claire. 2006. *Gas Turbines in Simple Cycle & Combined Cycle Applications.* Department of Energy, National Energy Technology Laboratory.

V. Glazar, V. Mrzljak, T. Gubic. July 2019. "Thermodynamic Analysis of Combined Cycle Power Plant." *14th International Conference on Heat Transfer, Fluid Mechanics and Thermodynamics.*

Veronika Eyring, Sandrine Bony, Gerald A. Meehl, Catherine A. Senior, Bjorn Stevens, Ronald J. Stouffer, and Karl E. Taylor. 2016. "Overview of the Coupled Model Interpomparison Project Phase 6 (CMIP6) Experimental Design and Organization." *Geoscientific Model Development Vol. 9, Iss. 5* 1937-1958.

(END APPENDIX C)