Load Consumption Prediction Utilizing Historical Weather Data and Climate Change Projections

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***Abstract*—The weather impact a major factor in operation of power systems. From the long-term planning perspective, it is not enough to predict whether impacts caused by short-term changes in the atmosphere but one also needs to account for the impact of long-term climate change as well. This paper demonstrates how to utilize the historical weather data and climate change projections in a large (macro) geographical area to predict future load patterns in a relatively small (micro) geographical area. The results show that the impact of temperature rising can have either positive or negative impact on the load, and the deviations may be large depending on the projected climate change data.**

***Index Terms*—Big data, data analysis, meteorology, power demand, power system planning.**

I. INTRODUCTION

Weather event caused by the change in atmosphere conditions in a short period, generally from minutes to months, can significantly affect the power system operation. From the long-term planning perspective, the climate change impacts should also be considered. Climate is actually a long-term weather pattern for a particular area [1]. The latest 2015 Climate Change Impacts and Risk Analysis (CIRA) report shows some key findings under the CIRA Reference scenario [2]:

- Global mean temperature is projected to increase by over 9 °F by 2100.
- The demand for air conditioning will be more significant than the decreases in electric heating requirement.
- Average electricity demand in the U.S. is projected to increase by 1.5% to 6.5% by 2050.

Several studies in the past were focusing on estimating and demonstrating the impacts of climate change on power system and how to mitigate them. Thorsteinsson *et al*. [3] discussed the assessments of climate changes on future development of renewable energy resources in the Nordic and Baltic regions. Nguyen et al. [4] described a modeling approach to mitigate climate impact by using plug-in hybrid electric vehicles, load management programs, energy efficiency, high renewable energy penetration, and energy storage. Das et al. [5] characterized how energy service companies may optimize the power shortage problem during peak load time. Overybye *et al*. [6]-[7] identified future research areas to clarify (1) the capability of power system infrastructure to respond to climate change and extreme weather events, (2) impacts of climate change on system operations, (3) utilization of renewable and alternative energy resources, and (4) impacts of electricity market and policy to multiple aspects. Morgan et al. [8] looked at the options for reducing greenhouse gas (GHG) for the next 50 years for power industry. Khan et al. [9] conducted a parametric approach to study the effect of temperature on the generation efficiency and its impact to economy in Australia. Jerez et al. [10] assessed the climate change impacts on photovoltaic (PV) power in Europe using European branch of Coordinated Regional Climate Downscaling Experiment (EURO-CORDEX) data and PV modeling. Bloomfield et al. [11] illustrated the climate variation impacts in the yearly scale on load and generation for Great Britain. Chandramowli et al. [12] provided an overview regarding impacts of climate change on power system planning.

The change of climate and the demand of electricity are greatly related. Particularly, the rising of temperature caused by climate change will have a major impact on cooling. Lu et al. [13] projected the residential and commercial building consumption using multidisciplinary modeling approach. Sullivan et al. [14] developed a methodology to quantify the impact of climate change on electric load in the U.S. across 300 transmission zones and 16 seasonal and diurnal time periods. Crowley et al. [15] investigated the estimation of higher temperature impact on the demand using hourly and annual data where the scenarios were constructed to present the impact within 2 °F increase. Auffhammer et al. [16] demonstrated a comprehensive literature survey regarding climate change impacts on consumption.

While aforementioned research discussed the impact of climate change on load and generation, none of them has utilized both historical weather data and projected climate change data for future load consumption prediction. It is imperative to understand how to use the climate model while looking at long-term planning, as well as predicting for the near future.

This work was supported in part by the Nation Science Foundation (NSF) award EEC-1041877 through a project titled “The Use of Big Data for Outage management in Distribution Systems”, under a contract A12-0044-S005 from Center for Ultra-Wide-Area Resilient Electric Energy Transmission Networks (CURENT) of University of Tennessee.*)*

This paper studies the impact of historical and predicted future temperature data to illustrate the climate change impact, utilizing linear regression learning method. The data analytics uses the historical temperature and summer peak load data from 2008 to 2015 to perform a climate impact study. The hypothesis is that the power consumption anomaly will be positive for Harris County since the temperature is expected to grow. To validate the hypothesis, the power consumption anomaly regarding temperature rise in the historical data will be analyzed and correlated with predicted climate data.

The geographical scale is another key issue. Meteorologists and climatologists in general look at climate change studies in a relatively wide geographical scale (e.g. Southern Plains of USA). For a given utility company, the planning may need to be done within a relatively small area (e.g. size of a county) [17]. In this study, Harris County is chosen as the micro geographical area under study. This county is the most populous county in the State of Texas, and the third most populous county in the USA [18]. Harris County is a relatively small area comparing with the macro area of the south plains.

The paper is organized as follows. Section II discusses the background. Section III illustrates the climate impact on the peak temperature. Section IV evaluates the impact of temperature on peak load. Section V contains conclusions.

II. Background

A. Coupled Model Intercomparison Project Phase 5 Data

Within the world climate Research Programme (WCRP), the Working group on Coupled Modeling (WGCM) has developed the Coupled Model Intercomparison Project (CMIP), which is the standard experimental protocol for analyzing coupled Atmosphere-Ocean General Circulation Models (AOGCMs) [19]. The data from CMIP is one of the most known source and is widely use in various climate studies. Other climate data sources can be found in [12].

The latest climate data from CMIP Phase 5 (CMIP5) is used in this paper. The data access, the modeling groups, and the syntax of data reference can be found in [20]-[23]. The term Representative Concentration Pathway (RCP) is adopted in the Fifth Assessment Report (AR5) issued by United Nations Intergovernmental Panel on Climate Change (IPCC), where AR5 consists a series of reports relying on CMIP5. The RCP is the latest term to be used for foreseeing projections regarding pathways of GHG emissions and atmospheric concentrations, driven by socio-economic development and climate policy [24]. RCPs contain several scenarios including one stringent mitigation (RCP 2.6), two intermediate (RCP 4.5 and RCP 6.0), and one with very high GHG emissions (RCP 8.5). RCP 4.5 is defined a scenario that stabilizes radiative forcing at 4.5 Watts per meter squared (W/m^2) by the year 2100 without ever exceeding that value [25]. In different scenarios of RCP, RCP 4.5 is seen as a stabilization scenario which assumes the imposition of emission mitigation from climate policies [25]. In this paper we have chosen to use the predicted data generated using RCP 4.5.

While there is a number of models from different groups [20] in CMIP5, some comprehensive studies [26] have shown that there is no single model standing out as particularly better or worse, while some models may outperform the other models for certain parameters depending on their resolutions. Considering the number of physical reactions and the level of model complexity to describe various meteorological phenomena, the tuning of parameters in the climate model simulation is not straightforward and involves human intervention in many cases.

B. Climate Studies Done Using CMIP5

Several papers are focusing on different weather parameters in climate studies using CMIP5 models and data. Langenbrunner et al. [27] focused on midaltitude pacific storm track. Prein et al. [28] looked at future intensification of extreme hourly precipitation. Seager et al. [29] studied the North American hydroclimate changes. Thibeault et al. [30] investigated the climate extremes in the northeast USA. Ting et al. [31] discovered North Atlantic Hurricane Potential Intensity Variation. Kooperman et al. [32] discussed the response of US summer precipitation to climate change. Maloney et al. [33] provided a comprehensive evaluation regarding North American climate assessment in CMIP5 experiments. It is notable from the past studies that the precision of temperature increase estimation is higher than other weather variables (e.g. precipitation).

There are very few studies done using CMIP5 climate data for power system related applications, and if they are done, they usually look at a very large (macro) geographical scale. Clack et al. [34] discussed how to use the proposed model for unit commitment and economic dispatch for transmission networks. Bartos et al. [35]-[36] looked at how the rising temperature may impact the load and generation in the western part and the entire USA.

III. Climate Change Impact on Future Peak Load

In this section, the anomaly of power consumption data from the historical load data and historical climate data will be firstly identified. Then the prediction of future climate change will be done using new data analytics techniques. Fig. 1 shows the flowchart of the proposed methodology.

A. Historical Load and Climate Change Data

The peak load data comes from the distribution network in Harris County from 2008 to 2015 (detailed in [17]). The average maximum temperature $\overline{T_{\max}}$ on the corresponding

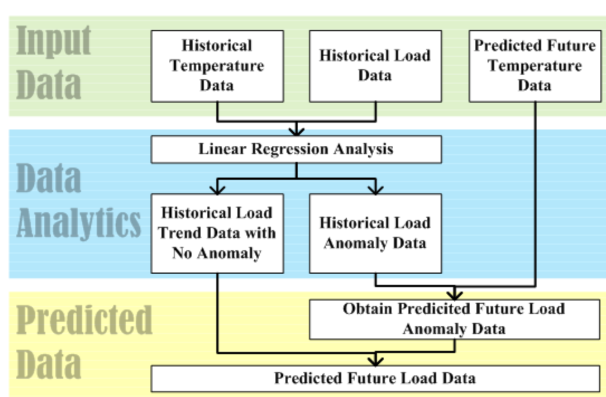

Figure 1. Flowchart of study.

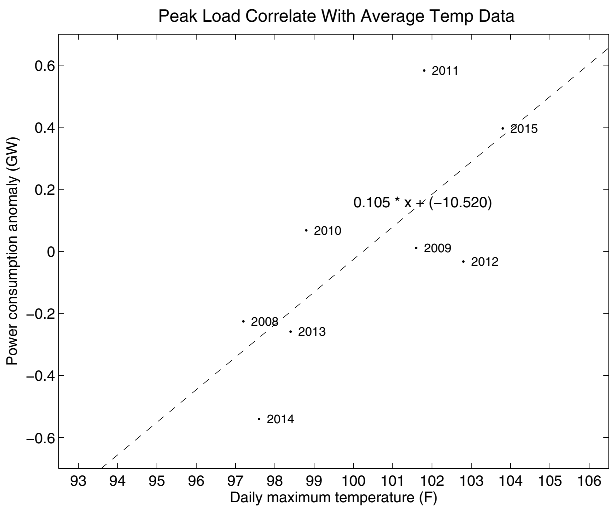

Figure 2. Linear regression studies between historical $\overline{T_{\max}}$ and peak load anomalies data.

date from the 5 weather stations including Houston William P. Hobby Airport (HOU), Baytown, Sugar Land Regional Airport (SGR), Houston Intercontinental Airport (IAH), and Pearland Regional Airport (LVJ) is obtained to perform linear regression studies, IAH is the only station located within the studied network, and the others are located in the surrounding areas. The historical temperature data is obtained from Daily Summaries data of Climate Data Online (CDO) database maintained in National Centers for Environmental Information (NCEI) [37].

The historical peak load data is detrended to analyze the anomalies to see if the change of $\overline{T_{\max}}$ and the increase rate of load consumption are correlated. In this case, the load data is subtracted from the data with the fit line, and the fluctuations in the data trend can be analyzed. Fig. 2 shows the power consumption anomalies versus $\overline{T_{\max}}$.

B. Predicted CMIP5 Data

Table I shows the CMIP5 data from various models [20]. The *tasmax* data, monthly mean of the daily-maximum near-surface air temperature is used for the study. From each model in Table I, for each year between 2016 and 2100, the largest *tasmax* among Jun, July and August of that year is used to represent the peak temperature of such year (Fig. 3). In other words, the peak temperature for the rest of 85 years in the current 21st century is obtained for the predictive analysis. Fig. 4 shows the processed data where the corresponding data set number is shown in Table I. For the CMIP5 data used from various modeling groups, RCP scenario is RCP 4.5 (Section II-A), and the ensemble parameter is r1i1p1 [22]. The resolution is the distance between each grid point and its adjacent grid points.

C. Predicted Results

For the better visualization purpose, the predicted results are separated into 3 different groups. Figs. 5, 6, and 7 show the predicted peak load data for tmax01 to tmax08, tmax09 to

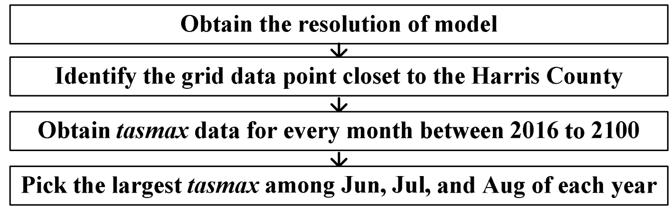

Figure 3. CMIP5 data processing.

TABLE I. CMIP5 DATA INPUT.

Data Set	Model Name	Atmospheric Grid Resolution (Latitude, Longitude)
tmax01	ACCESS1.0	1.250, 1.875
tmax02	ACCESS1.3	1.250, 1.875
tmax03	CMCC-CM	0.749, 0.750
tmax04	CMCC-CMS	3.711, 3.750
tmax05	CNRM-CM5	1.401, 1.407
tmax06	GISS-E2-H	2.000, 2.500
tmax07	GISS-E2-H-CC	2.000, 2.500
tmax08	GISS-E2-R	2.000, 2.500
tmax09	GISS-E2-R-CC	2.000, 2.500
tmax10	HadGEM2-AO	1.250, 1.875
tmax11	HadGEM2-CC	1.250, 1.875
tmax12	HadGEM2-ES	1.205, 1.875
tmax13	INM-CM4	1.500, 2.000
tmax14	IPSL-CM5A-LR	1.895, 3.750
tmax15	IPSL-CM5A-MR	1.268, 2.500
tmax16	IPSL-CM5B-LR	1.895, 3.750
tmax17	MIROC-ESM	2.791, 2.813
tmax18	MIROC-ESM-CHEM	2.791, 2.813
tmax19	MIROC5	1.401, 1.406
tmax20	MPI-ESM-LR	1.865, 1.875
tmax21	MPI-ESM-MR	1.865, 1.875
tmax22	MRI-CGCM3	1.121, 1.125
tmax23	NorESM1-M	1.895, 2.500

tmax16, and tmax17 to tmax23, respectively. The left-hand part is the historical peak load data from 2008 to 2015. The right-hand part is the future predicted data based on different models of temperature data. The convex hull shows the upper and lower bounds of the data set.

D. Discussion

The CMIP5 data from different models in Fig .4 show some variations from each other. Some groups show higher temperature increase than others. Some groups demonstrate the tendency of higher temperature over the years while some are medium and low. The fluctuations are also different. All these charterers in the input data are reflected in the output data shown in Figs. 5 to 7. In Fig. 2, the power consumption anomaly could be negative if the historical $\overline{T_{\max}}$ is smaller than 100.19 °F. Since the data from more than 50% of model is not greater than 100.19 °F, the predications of those in Figs. 5 to 7 will show a smaller than average increase rate due to negative power anomalies.

Even though the temperature increase in most models is smaller than the global average predication (9 °F by 2100 in CIRA report in Section I), it does not mean that the predictions from these models are not accurate, depending on how the models are developed and simulated (Section II-A). It is possible that the temperature increase is not as much as global

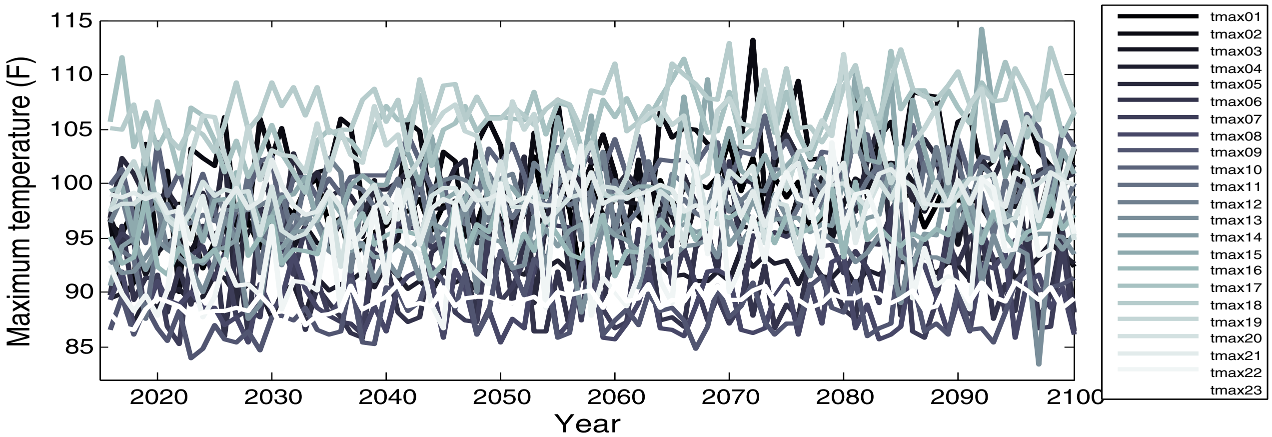

Figure 4 Processed CMIP5 data from 23 different models.

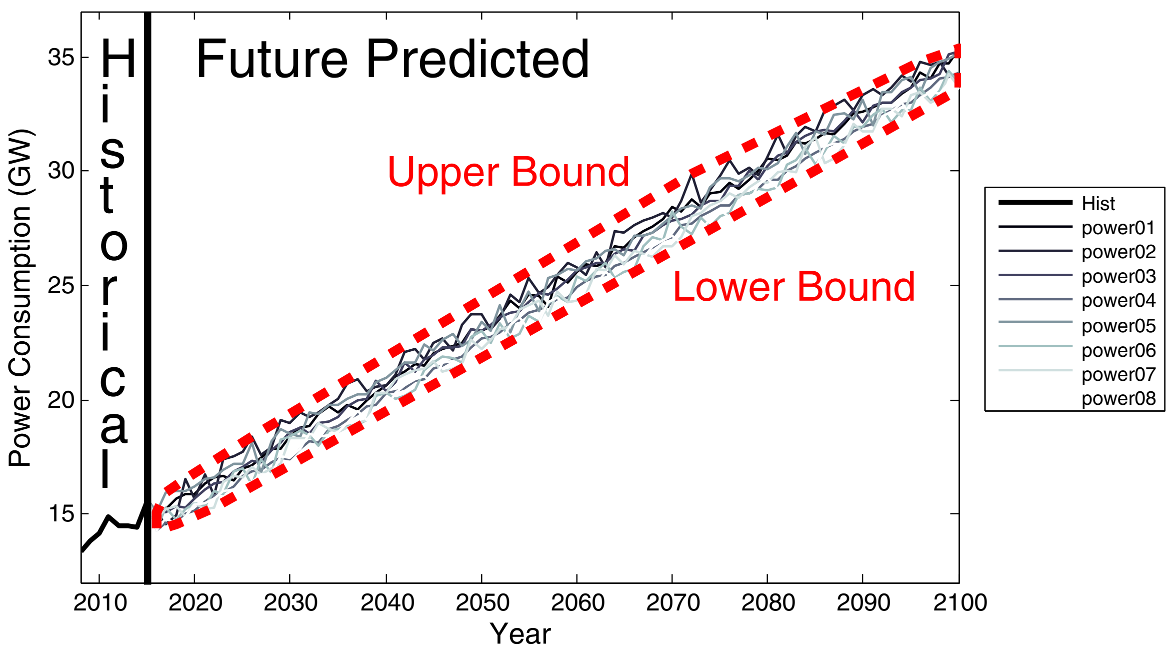

Figure 5. Predicted load consumption from 2016 to 2100 for model group tmax01 to tmax08.

average in Harris County. This actually leads to a very important conclusion: the impact of temperature on the load consumption anomaly could result in either increase or decrease: the largest power anomaly deviations are 1.465 GW and -1.777 GW. This actually deny the hypothesis set in the introduction: the power anomaly could be negative depending on the rising rate of the temperature.

The upper bound in Fig. 7 actually has a relatively larger value comparing to the ones in Fig. 5 and 6 from roughly 2016 to 2060. In between 2060 and 2080 the order starts to change interchangeably. After 2080 the upper bound in Fig. 6 becomes the largest followed by the ones in Fig. 7 and in Fig. 5. The order of lower bounds is in general the same: the lower bound in Fig. 7 is the largest, the one in Fig. 5 are the second largest, and the one in Fig. 6 is the smallest. Different bounds regarding the predictions are related to how CMIP5 models design the parameters (described in Section II-A) and the uncertainties in the input data (described below).

The predicted CMIP5 data is the largest monthly mean of the daily-maximum temperature. The reason for using the monthly mean instead of daily maximum is because the target is regarding the peak load average for the month. However, the historical temperature and load data is the highest peak load data in the year with the temperature of that day. Since the daily maximum will definitely be greater than the monthly mean, it can be expected that the predicted power consumption would be higher than the results given in Figs. 5, 6, and 7.

There are several uncertainties in the input data which are beyond this study and may be taken into account in the future:

- As shown in Table I, the number of samples of historical peak load data is very small. This enhances the difficulties in providing a more detailed study regarding the power consumption anomaly due to the climate variation.
- As specified in Section II-A, the variation regarding predicted temperature between each climate model in Table can be more precisely quantified.

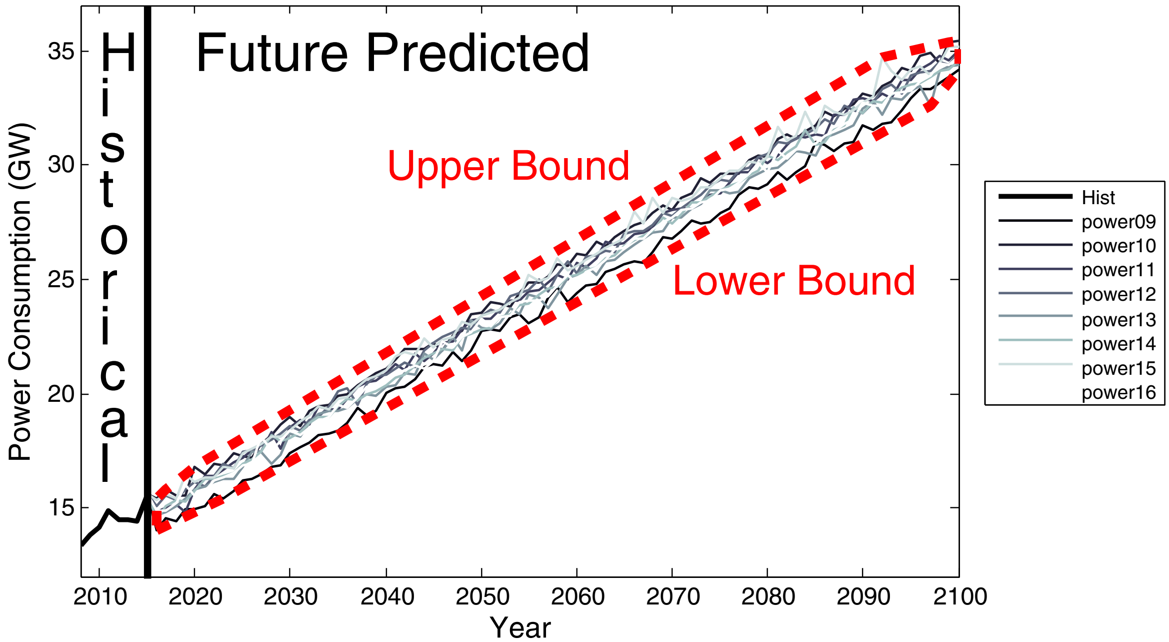

Figure 6. Predicted load consumption from 2016 to 2100 for model group tmax09 to tmax16.

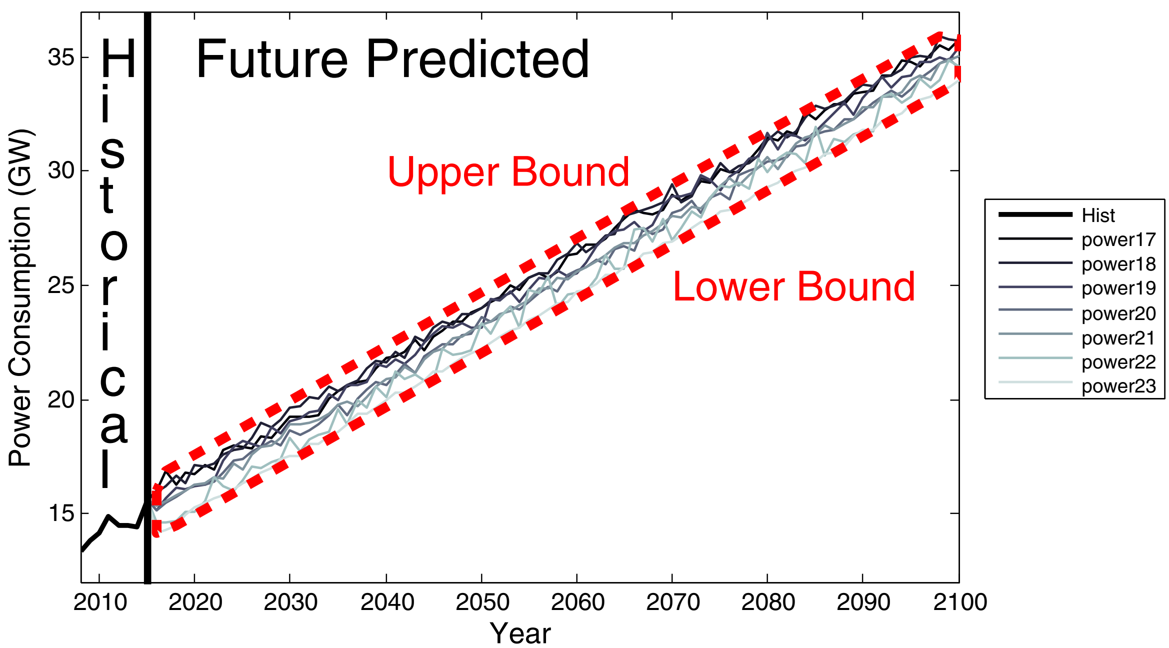

Figure 7. Predicted load consumption from 2016 to 2100 for model group tmax17 to tmax23.

- The temperature data taken into account is only one grid point, which may not be within Harris County but nearby depending on the model resolution. The precision of the grid resolution and how it may affect the temperature parameter prediction particularity should be assessed and taken into account.

IV. Conclusion

This paper makes several contributions:

- The framework to predict future peak load consumption is proposed. We utilize both historical and predicted temperature data, and historical peak load data to access the power consumption anomalies and apply them to future peak load predictions.
- The predicted CMIP5 data shows that the increase in temperature in Harris County may not be as much as the global mean, where most models show smaller numbers.
- The temperature rising impact on the peak load can be either positive or negative. The deviations can be more than 1 GW in the distribution networks, which is relatively large. Therefore, the uncertainties in the input data should be further quantified and assessed in the future study.

ACKNOWLEDGMENT

The authors would like to acknowledge CenterPoint Energy for providing the historical peak load data.

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