Final Report: Developing Integrated Assessments of Water and Energy in Ohio

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1 Summary

Water and energy are intrinsically linked in modern energy systems, where demand for one results in a demand for the other. These demands will depend on the weather (e.g., air-conditioning), the supply of water (e.g., precipitation), and the type of cooling technology used in a power plant. The problem is that our understanding of these linkages is far from complete. The overall objective of this project is to improve our understanding of how electricity demand, and the demand for water by thermoelectric power plants that supply electricity, depend on weather in the short and long term. The research comprises two major parts. The first part comprises of constructing a statistical model that relates regional electricity demand to weather variables (temperature, relative humidity, wind speed) in a parametric form. The model was based and tested on more than ten years of hourly data in two transmission zones in the Pennsylvania-New Jersey-Maryland (PJM) Interconnection. One novel feature of the model is that the statistical technique employed enables empirical estimation of the base temperatures in cooling-and heating-degree hours, which are two traditional metrics used in estimating electricity demands associated with cooling and heating. The result indicates that a piecewise linear function is approximately valid for describing the relationship between electricity demand and temperature, with a relatively flat region over the medium temperatures that define a "comfort zone" between heating and cooling. The result also gives quantitative measures of the effects of past temperatures, relative humidity, and wind speed on electricity demand. The second part comprises of connecting the electricity demand to the water demand of power plants. We have acquired monthly facility-level water demand data from the Energy Information Administration (EIA) database and the Ohio Department of Natural Resources (ODNR). Since the data are of low quality, they are currently being cross-examined with a variety of resources (literature values, google earth, previously corrected datasets, etc.) for quality control and correction, and as yet partially analyzed. Conversations are ongoing with AEP (initiated in the second quarter of this project) to acquire daily facility-level water data.

2 Problem and research objectives

2.1 On the relationship between electricity demand and weather variables

Accurate electricity load forecasts have a number of applications. Forecasts on the timelines of days to several years are important to inform electricity dispatch scheduling, capacity expansion by utility companies, and state-level policy-making (Beccali et al., 2008; Chandramowli and Felder, 2014; Dordonnat et al., 2008). On the timeline of decades, models of electricity load can help understand the potential impacts of, and thus adaptation needs to, climate change (Auffhammer and Aroonruengsawat, 2011; Braun et al., 2014; Ruth and Lin, 2006). One way to characterize how electricity demand depends on temperature is to use the concept of degree days (the counterparts on hourly scale are called degree hours). Heating Degree Days (HDDs) are calculated as the number of degrees that a day is below a reference temperature, and Cooling Degree Days (CDDs) are calculated as the number of degrees that a day is above a reference temperature. Together, these two metrics represent the relationship between energy demand and temperature as a V-shaped distribution about the reference temperature. This HDD/CDD approach and has frequently been used in decadal projections of energy demand and in load forecast studies (Amato et al., 2005; Mirasgedis et al., 2006; Pardo et al., 2002; Ruth and Lin, 2006; Scapin et al., 2015; Shorr et al., 2009; Vu et al., 2014).

One difficulty in using HDDs and CDDs is that the base temperatures are difficult to estimate. Studies have used established reference temperatures (18.3 ^{o}C), estimated the reference temperature by visual examining the data, or determined the reference temperature by maximizing some criterion for model performance (Amato et al., 2005; Mirasgedis et al., 2006; Scapin et al., 2015; Shorr et al., 2009; Vu et al., 2014). Most of these types of studies assumed that the reference temperature for HDDs is the same as the reference temperature for CDDs (Amato et al., 2005; Mirasgedis et al., 2006; Shorr et al., 2009; Vu et al., 2014). It has been noted that geographical variations can exist in base temperature (Brown et al., 2016), and that the uncertainty in base temperature should be considered during the model estimation process (Woods and Fuller, 2014). Also, past studies that used smooth transition regression models, which replace the V-shaped transition from HDDs to CDDs by parameterized logistic or exponential functions, suggested that a "comfort zone" exists at intermediate temperatures where the electricity demand is less sensitive to changes in temperature (Bessec and Fouquau, 2008; Moral-Carcedo and Vicéns-Otero, 2005). This means that different base temperatures for HDDs and CDDs may be needed.

While temperature is generally considered the most important weather determinant of electricity load, lagged temperatures, humidity, wind speed, solar radiation, precipitation, and/or air pressure can have secondary influences. The decadal-scale studies usually only used temperature to capture the major effect of climate change, in addition to socioeconomic factors (e.g. electricity price, population) (Amato et al., 2005; Auffhammer and Aroonruengsawat, 2011; Franco and Sanstad, 2007; Ruth and Lin, 2006). Studies focusing on shorter time scales generally included some of the secondary factors to increase the accuracy of the predicted electricity demand (Beccali et al., 2008; Dordonnat et al., 2008; Mirasgedis et al., 2006; Psiloglou et al., 2009; Scapin et al., 2015; Vu et al., 2014), but such studies tended to focus more on the skill of prediction than understanding of the functional form.

Therefore, one objective of the study is to empirically determine the base temperatures of heating- and cooling-degree hours (HDHs, CDHs) using a segmented regression technique (Muggeo, 2008). This method allows different base temperatures for HDHs and CDHs, and is robust because the uncertainty in base temperatures is considered during the model estimation process (Muggeo, 2008). Compared to the smooth transition regression models, the piecewise linear assumption in the degree days concept is not modified in segmented regression (Muggeo, 2008). The second objective is to determine the effects of temperature, past temperatures, relative humidity, and wind speed on electricity load, and their relative importance. To achieve these, a model was first developed using only temperature, and then the model was extended to include past temperatures, relative humidity, and wind speed as additional predictors of electricity load.

2.2 The water demand of thermoelectric power plants

Thermoelectric power plants traditionally have significant water demand. In 2010, the water withdrawal by thermoelectric power plants accounted for 45% of the national total water withdrawal, though only a small portion of the withdrawal is consumptive (e.g. lost to evapotranspiration) (Maupin et al., 2014). Water consumption by the thermoelectric sector is small compared to agriculture, but is still larger than all other industrial consumptions combined, and is expected to grow by 40~60% by the 2030s (The Great Lakes Commission, 2011). This high water demand means that the thermoelectric sector is vulnerable to water scarcity caused by simultaneous demand from multiple end-use categories (e.g. irrigation, public supply, the aquatic ecosystem), and by weather variability and climate change. Instances where the development of new power plants was hampered by lack of cooling water are increasing (Scott and Huang, 2007). In a few extreme cases, power plants have curtailed electricity production or shut down due to high water temperature or low streamflow (see Förster & Lilliestam 2010).

The water intensity of thermoelectric power plants is generally characterized by water withdrawal and consumption factors, which, respectively, are the amount of water withdrawal and consumption per unit net electricity generation. Annual water withdrawal and consumption factors for power plants in the US have been synthesized or estimated in a number of past studies, and are found to depend the power generation technology, cooling system, and the existence of additional features such as carbon capture and storage (Diehl and Harris, 2014; Macknick et al., 2011; Strzepek et al., 2012). Within each of the categories, the water withdrawal and consumption factors are still highly variable, and unexplained discrepancy exists between the factors calculated from actual water use data and the factors estimated by literature (Averyt et al., 2013; Macknick et al., 2011). Our inadequate understanding of the water withdrawal and consumption factors means that current national estimation of the water use by thermoelectric power plants is highly uncertain.

Therefore, the objective of the study is to improve our understanding of the water use by thermoelectric power plants by examining the influence of weather variables. A statistical model will be constructed that relates weather variables (e.g. temperature, atmospheric pressure, humidity) to the cooling water withdrawal and consumption factors, while controlling for the known time-invariant factors such as power plant configuration and cooling technology.

3 The response of hourly electricity load to meteorological variables in the PJM Interconnection

3.1 Methodology

The temperature-only and the extended electricity demand models were estimated using the time series routine (segmented.Arima) in the R-package "segmented" (version 0.5.1.1) (Muggeo, 2008) under the R 3.2.0 environment. The basic formulas are:

$$E_{t,j} = a_j + \sum_{m=1}^{11} b_{j,m} M_m + \sum_{w=1}^{w=6} c_{j,w} W_w + \boldsymbol{X_{t,j}} \boldsymbol{\beta_j} + \zeta_{t,j}$$

$$\theta_p(B) \Theta_P(B^S) \zeta_{t,j} = w_q(B) W_Q(B^S) e_{t,j}$$

where $E_{t,j}$ is electricity load on day t and hour j; a_j is the intercept, interpreted as the base load on any Sunday in December; M_m, m=1,2,...,11, are the monthly dummies, equal to 1 for January through November, respectively, and 0 otherwise; $b_{j,m}$ are coefficients that describe the fixed monthly variations in base load; W_w, w=1,2,...,6, are the weekday dummies, equal to 1 for Monday through Saturday, respectively, and 0 otherwise; $c_{j,w}$ are coefficients that describe the fixed weekly cycles; $\boldsymbol{X_{t,j}}$ is the vector of meteorological variables (temperature, past temperatures, relative humidity, wind speed, interactions), and together with $\boldsymbol{\beta_j}$ describe the weather sensitive part of the load; $\zeta_{t,j}$ is the residual, and is assumed to follow a seasonal autoregressive moving average (S-ARMA) process, where $\theta_p(B)$, $\Theta_P(B^S)$, $w_q(B)$, and $W_Q(B^S)$ are polynomials of the backward shift operator B, p and q are the autoregressive and moving-average orders, P and Q are the seasonal autoregressive and moving-average orders, S is the seasonal cycle (here weekly), and $e_{t,j}$ is a white noise process with mean = 0 and some standard deviation.

For the temperature-only model, the weather-sensitive part is:

$$\boldsymbol{X}_{t,j}\boldsymbol{\beta}_j = \beta_{j,1}TP_{t,j} + \beta_{j,2}\left(TP_{t,j} - TP_{0,h}\right) * I\left(TP_{t,j} > TP_{0,h}\right) \\ + \beta_{j,3}\left(TP_{t,j} - TP_{0,c}\right) * I\left(TP_{t,j} > TP_{0,c}\right)$$

where $TP_{0,h}$ and $TP_{0,c}$ are the estimated breakpoints that correspond to base temperatures in the definition of HDDs and CDDs; $\beta_{j,1}$, $\beta_{j,2}$, and $\beta_{j,3}$ are regression coefficients.

For the extended model, the weather-sensitive part is:

$$\boldsymbol{X}_{t,j}\boldsymbol{\beta}_j = \beta_{j,1}TP_{t,j'} + \beta_{j,2}\left(TP_{t,j'} - TP_{0,h}\right) * I\left(TP_{t,j'} > TP_{0,h}\right) \\ + \beta_{j,3}\left(TP_{t,j'} - TP_{0,c}\right) * I\left(TP_{t,j'} > TP_{0,c}\right) + \sum_{\Delta=1}^{3} g_{j,\Delta} TP_{t-\Delta,j'} \\ + \sum_{m=1}^{11}\sum_{\Delta=1}^{3} h_{j,m,\Delta}\left(M_m \times TP_{t-\Delta,j'}\right) + k_j RH_{t,j} + l_j\left(TP_{t,j'} \times RH_{t,j}\right) + n_j WD_{t,j}$$

where the temperature part is the same as above, $TP_{t-\Delta,j'}$ is the temperature on day t-Δ and hour j', $RH_{t,j}$ is relative humidity on day t and hour j, $WD_{t,j}$ is wind speed, and $g_{j,\Delta}$, $h_{j,m,\Delta}$, k_j, l_j, and n_j are regression coefficients. This formula was determined after testing various types of interactions among the weather variables and monthly dummies, and was found to be a good trade-off between complexity and performance.

The two transmission zones investigated in the PJM Interconnection is displayed in Figure 1. The two transmission zones were selected because they sample the diversity in location and area of the transmission zones in the PJM Interconnection, and have relatively long records. The AEP zone has an area of about $1.34*10^5$ km^2 and a population of about $7.63*10^6$ in 2010; the PS zone about $3.35*10^3$ km^2 and a population of about $4.36*10^6$ (U.S. Cenus Bureau, 2010).

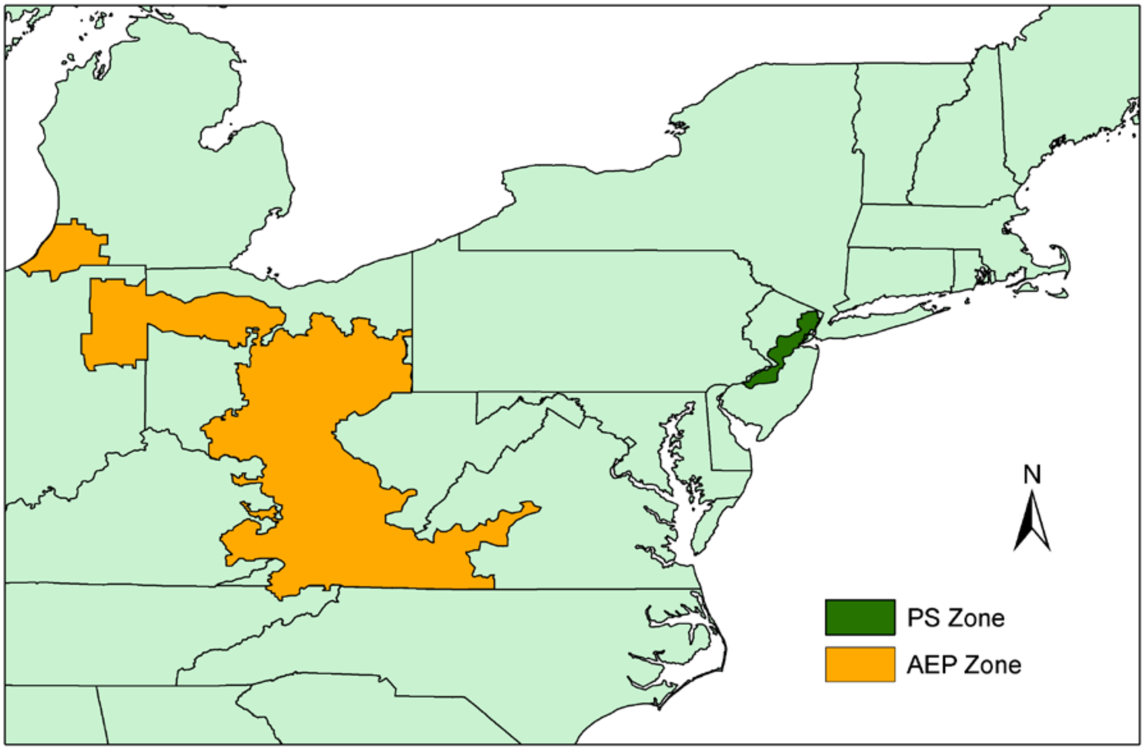

Figure 1. The transmission zones used in this study. Map adapted from the information on the PJM website (PJM, 2016). PS - Public Service Electric and Gas Company. AEP - American Electric Power Co., Inc.

3.2 Principal findings

Figure 2 shows the result of fitting the temperature-only model in hour 14 in the two transmission zones; the piecewise relationship is shown for a typical Sunday in December, a typical workday (Wednesday) in December, and a typical workday in July. The electricity response to temperature is characterized reasonably well by piecewise relationship. In the AEP zone, some high-load days on the heating arm were missed, which might be due to the fact that AEP zone spans a larger and more heterogeneous area than the PS zone. Electricity was used as the primary heating fuel in the southern part of the AEP zone, compared to natural gas in its northern part and the PS zone (EIA, 2015). This means that electricity demand could be more sensitive to temperature at the southern part of the AEP zone than the northern part, making the resulting data a mixture and therefore less easily captured by a single linear relationship

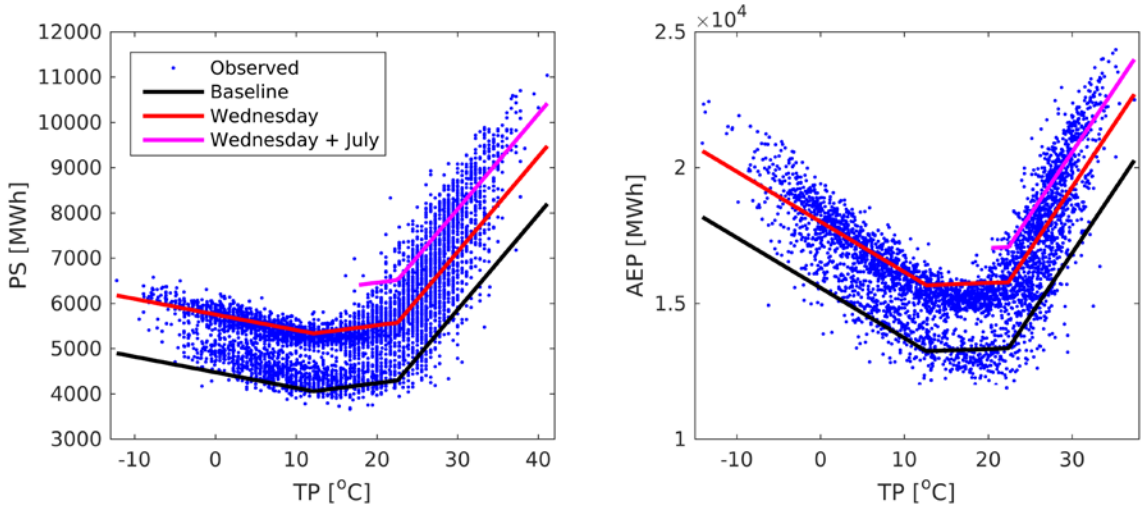

Figure 2. Observed relationship between temperature and electricity load at hour 14, and the fitted piecewise linear relationship for the baseline (i.e. December Sunday), Wednesday (December), and July Wednesday. The July relationship is only shown for July temperatures.

Figure 3 displays the estimated breakpoints ($TP_{0,h}, TP_{0,c}$) and slopes of the electricity response ($\beta_{j,1}$, $\beta_{j,1} + \beta_{j,2}$, $\beta_{j,1} + \beta_{j,2} + \beta_{j,3}$) of the temperature-only model and the extended model in the two transmission zones. In both transmission zones, the breakpoints were higher in working hours than in the night hours. In the PS zone, the diurnal range of the lower breakpoints was 10.2 ~ 15.8 °C, and of the higher breakpoints 17.8 ~ 23.2 °C. In the AEP zone, the diurnal ranges were 9.3 ~ 13.8 °C and 17.0 ~ 23.7 °C. Transition between the day and night hours occurred gradually. The higher breakpoints, corresponding to the base temperature for CDH, were significantly separated from the lower breakpoints, as indicated by the confidence intervals. This indicates the existence of a comfort zone. The slopes in the comfort zone (the middle line in the upper and lower left panels) were mostly statistically indistinguishable from 0 in the AEP zone. In the PS zone, the slope was positive, though much smaller than the slope of the cooling arm. These indicate that electricity load was relatively insensitive to temperature in the comfort zone.

Figure 3 also shows that the slopes of the heating arm were more negative in the extended model than in the temperature-only model; this was caused by the particular form of interaction between temperature and relative humidity ($TP_{t,j'} \times RH_{t,j}$). A more appropriate form of the effects of relative humidity has been identified and will be the subject of a follow-up study.

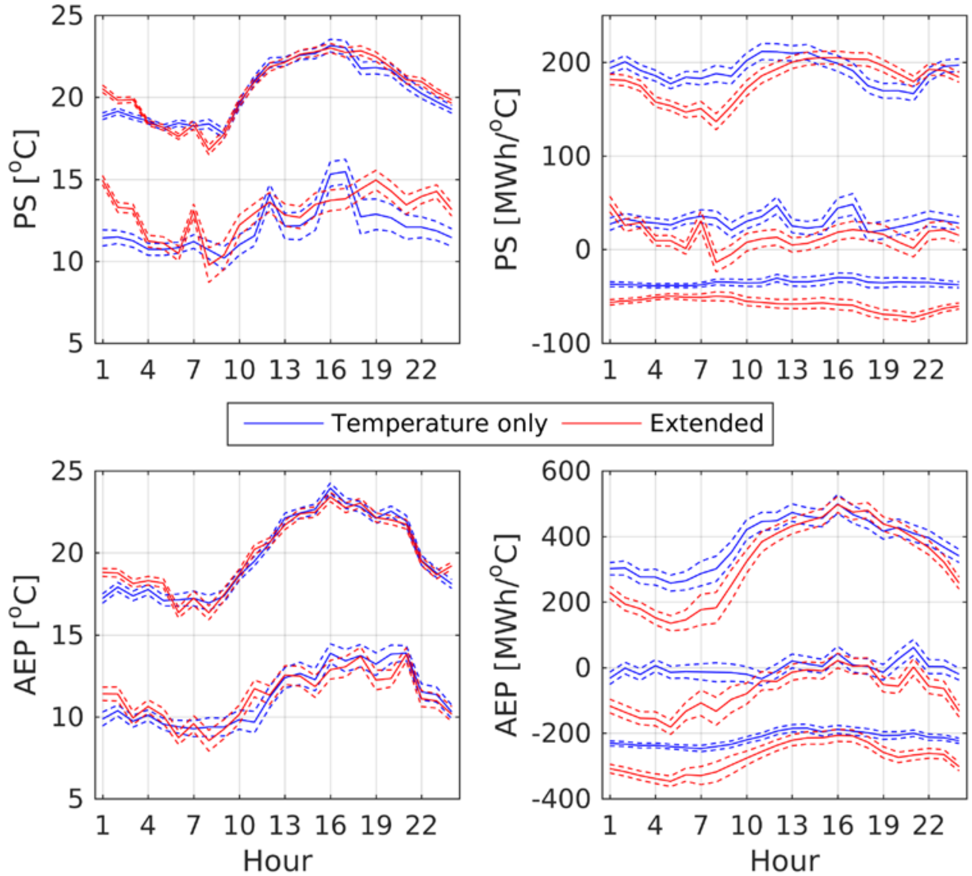

Figure 3. The estimated breakpoints and electricity response slopes in the PS and AEP zones by the temperature-only model and the extended model. Solid lines are the point estimations. Dashed lines show the 95% confidence intervals.

The effect of past temperatures on the same day is illustrated in Figure 4 for the extended model. The relationship between varying lags (*j-j'*) up to 7 hours and mean absolute percentage errors of the extended model is displayed. As can be seen, in the PS zone, electricity load was generally best predicted by temperature on the same hour, though some small lags appeared to exist between hours 3 and 6. In the AEP zone, the smallest errors were obtained at non-zero lags between hours 23 and 8, with the clearest effect being between hours 24 and 5. This lagged effect may be attributed to building insulation effects, where indoors temperature do not adjust immediately to outdoor temperature.

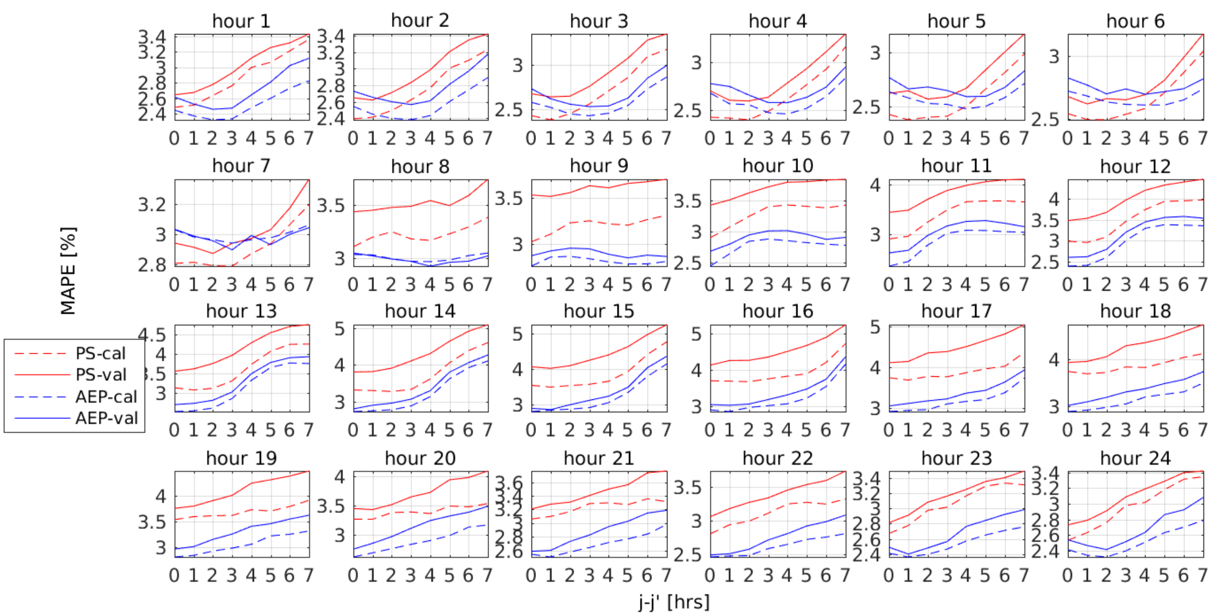

Figure 4. The effect of spacing between the hour of electricity observation *j* and the hour of temperature observation *j'* (*j*, *j'* = 1, 2, …, 24) on model MAPE. The MAPE was calculated from all the residuals in the calibration (cal) and validation (val) periods in the PS zone and the AEP zone.

The effect of past days' temperatures on electricity load are shown in Figure 5 for the selected hours 1, 10, 15, and 20. It shows that the past 1-day temperature has the strongest effect on electricity load, with clear positive coefficients in the summer months and negative coefficients in the winter months. The effects of past 2-3 days' temperatures were smaller, probably generally 0 in the winter months but sometimes positive in the summer months, provided that the uncertainty in the coefficients was similar to the uncertainty in the slopes. Overall, the slopes suggest that past days' temperatures amplified the relationship between present-day temperature and electricity load: higher past days' temperatures in winter resulted in lower electricity load, and in summer higher electricity load. This is consistent with the past observed cumulative effect in urban environments in summer (Li et al., 2014). In winter, the effect of past days' temperatures might be because some building managers only start heat supply after temperature was below a threshold for a certain amount of time. In past forecast studies at regional level, past days' cooling- and heating-degrees had also been found to positively correlate with electricity load (Dordonnat et al., 2008; Mirasgedis et al., 2006).

Judging by the number of standard deviations between the data points and x-axis, the summer cumulative effect was stronger in the PS zone than in the AEP zone. This might be because the PS zone area is more urbanized. The winter effect was stronger in the AEP zone, which might be related to the greater use of electricity for heating in the southern part of the AEP zone (EIA, 2015).

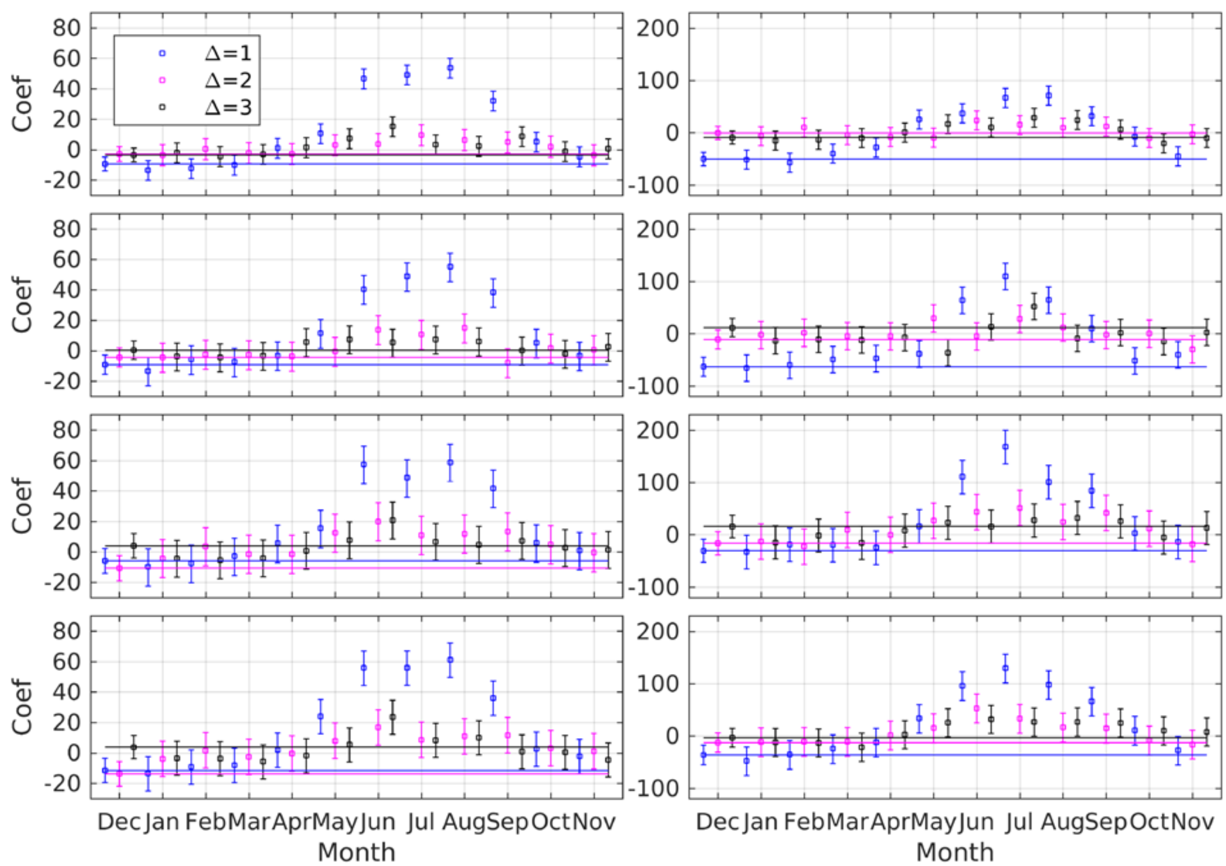

Figure 5. The slopes of electricity response to past days' temperatures ($TP_{t-\Delta,j'}, \Delta = 1,2,3$) at hours (top to bottom) 1, 10, 15, and 20 in the PS (left) and AEP (right) zones. Whiskers are ±2*standard deviations of the regression coefficients. Horizontal lines are reference lines extended from the December coefficients, relative to which other months' coefficients are plotted.

The effect of relative humidity in the extended model ($k_j RH_{t,j} + l_j(TP_{t,j'} \times RH_{t,j})$) cannot be interpreted based on each coefficient, because of the existence of interaction term. The estimated k_js were sometimes negative, but the estimated l_js were always positive. Figure 6 illustrates the relationships between this combined term and electricity load, and between this combined term and temperature. Due to its high collinearity with temperature, this term had a similar relationship with electricity load to temperature. This high collinearity was also identified as the cause of overestimation of the slope of the heating arm in Figure 3. In the high-temperature region, the term was positively correlated with electricity load. The results suggest that while the effect of relative humidity is temperature-dependent, the functional form needs further development. It is hypothesized that relative humidity may only show impact on electricity demand above a temperature threshold. Since the regression model (Muggeo, 2008) used in this study cannot estimate such a relationship, the hypothesized new model is expected to be tested in a follow-up study that also incorporates socioeconomic factors into the statistical model.

The effects of wind speed in the extended model is displayed in Table 1. In the PS zone, wind speed was positively correlated with the load in the night, but negatively correlated in some afternoon hours. In the AEP zone, wind speed was mostly positively correlated with load. The sign of the relationship would have depended on whether the cooling effect of wind was more dominant in winter (causing higher electricity load) or in summer (causing lower electricity load). Compared to other terms, the effects of wind speed is minor and can probably be ignored in long-term prediction.

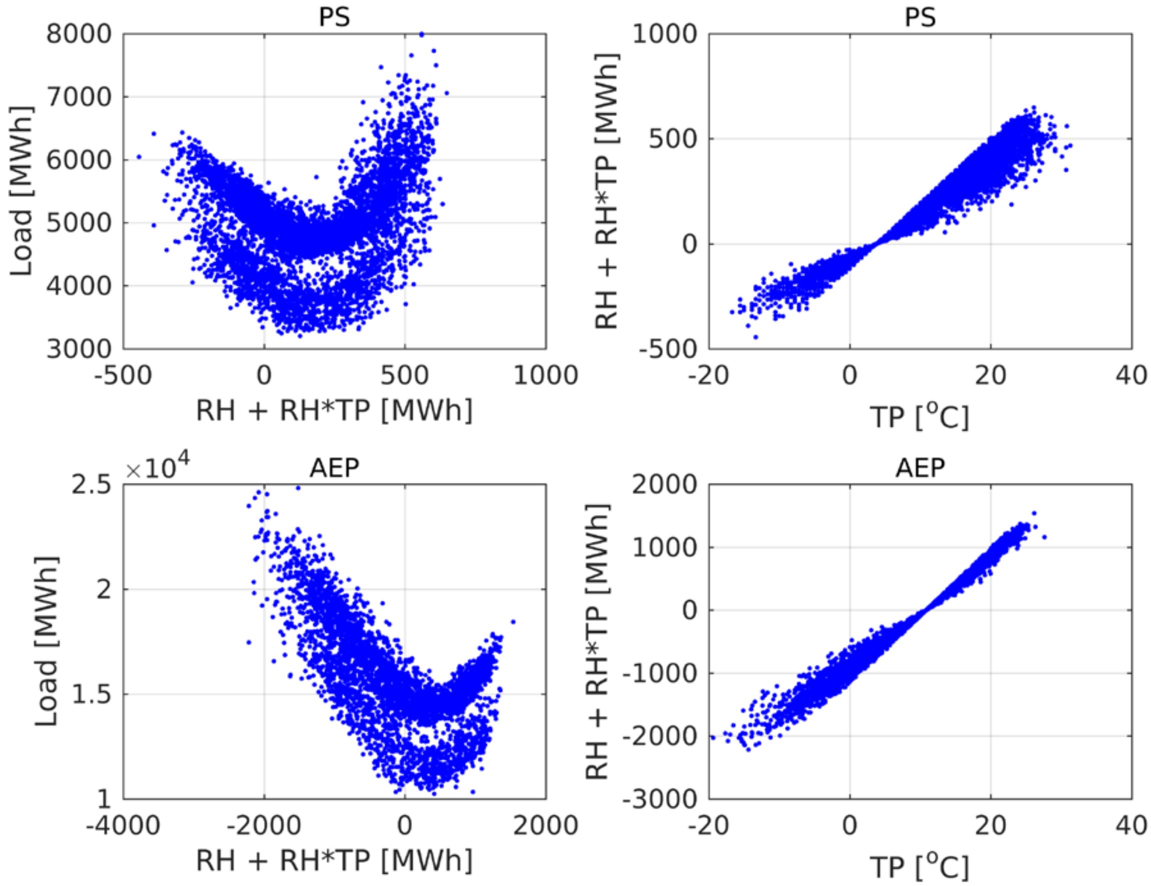

Figure 6. The relationship between $k_j RH_{t,j} + n_j(TP_{t,j'} \times RH_{t,j})$ and electricity load or temperature in the PS and AEP zones at hour 8.

Table 1. The regression coefficients of wind speed in the PS and AEP zones.

Hour	PS		AEP		Hour	PS		AEP	
	n_j	*t* value	n_j	*t* value		n_j	*t* value	n_j	*t* value
1	5.12	1.29	14.3	4.769	**13**	-4.78	1.83	25.65	6.349
2	3.05	1.16	14.57	4.661	**14**	-3.91	1.88	19.26	6.979
3	4.24	1.11	7.803	4.494	**15**	-4.86	2.08	20.77	7.428

4	3.60	1.07	7.692	4.69	**16**	-3.99	2.20	20.45	7.073
5	3.77	1.08	7.885	4.964	**17**	-5.93	2.36	16.69	7.208
6	4.22	1.14	-8.878	5.68	**18**	-6.88	2.48	16.59	7.303
7	3.56	1.40	-13.16	7.539	**19**	-3.17	2.33	22.73	7.39
8	4.69	1.83	-11.65	8.556	**20**	-0.77	2.16	27.96	7.186
9	5.01	1.82	2.936	8.282	**21**	-1.54	1.95	29.58	6.816
10	1.51	1.78	6.568	6.885	**22**	-0.29	1.78	25.37	6.463
11	-0.03	1.73	22.5	6.428	**23**	1.54	1.59	18.07	5.577
12	-2.83	1.74	29.94	6.19	**24**	3.15	1.42	16.87	5.024

4 The water use of thermoelectric power plants

4.1 Methodology

A version of corrected EIA Form 923 water use data for the year 2008 (Rogers et al., 2013) have been examined for the distribution of thermoelectric power plants and cooling technologies in the US. Water use in this dataset is representative of ~30% to ~50% of the US thermoelectric power plants, due to missing data in the original EIA Form 923. This dataset is on the annual level and therefore cannot adequately reflect the influence of weather variables. The original EIA Form 923 contains numerous errors in the locations of power plants, cooling systems, and water use values. Those are expected to be corrected following the approach of past studies (Averyt et al., 2013; Diehl et al., 2013).

4.2 Principal findings

Figure 7 and Figure 8 show some spatial features of the water withdrawal and consumption factors according to the preliminary dataset (Rogers et al., 2013). Overall, the coal-fired power plants tend to be located in the northeastern part of the country, while the more efficient natural gas power plants tend to be located in the southwestern part. More of the natural gas power plants tend to be cooled by recirculating technologies than coal-fired power plants. Along the coastlines, some once-through cooled power plants exist that use ocean water. It can also be seen that for the once-through power plants, the consumption factor is much lower than withdrawal factor, while for the recirculating power plants, the two factors are similar.

Figure 9 and Figure 10 show that a weak negative relationship exists between the water use factors of power plants and their capacity factors. This might be because the very infrequently used power plants are equipped with less efficient technologies to reduce the cost.

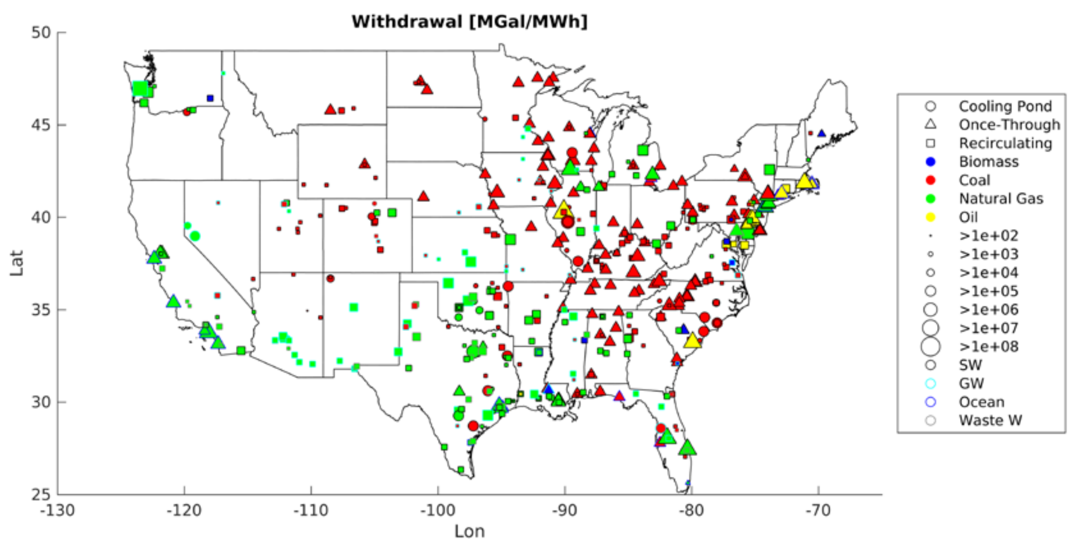

Figure 7. The spatial distribution of water withdrawal factors of the power plants (by size of the labels), as well as the cooling technologies, fuel type, and source of water (SW- surface water; GW – groundwater; Ocean – ocean; Waste W – wastewater).

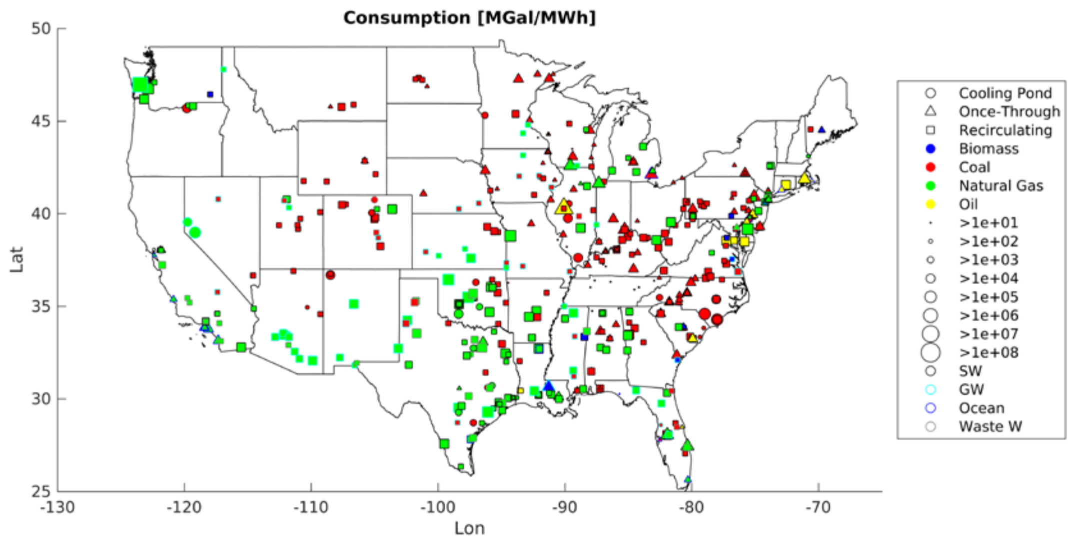

Figure 8. The spatial distribution of water consumption factors of the power plants (by size of the labels), as well as the cooling technologies, fuel type, and source of water (SW- surface water; GW – groundwater; Ocean – ocean; Waste W – wastewater).

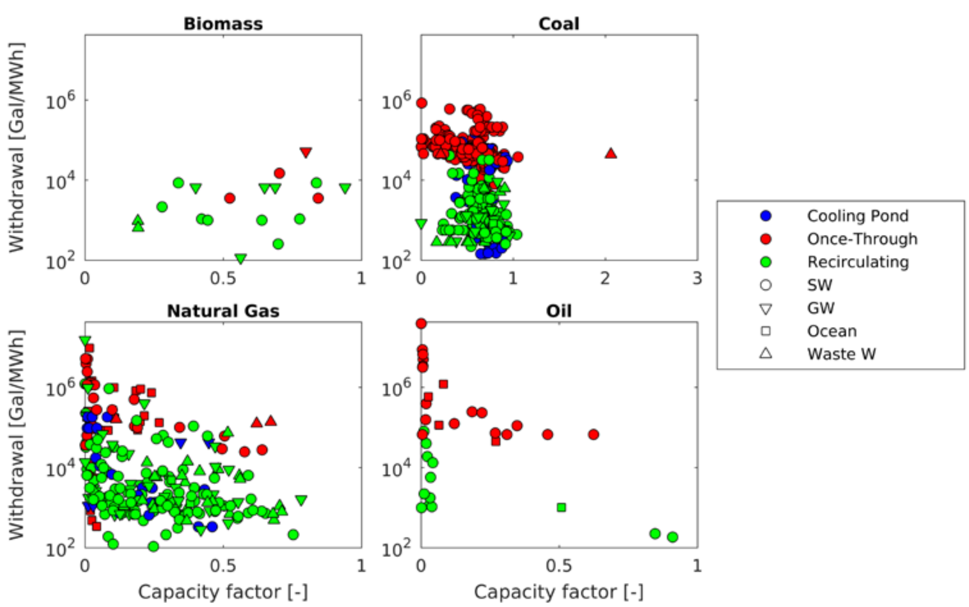

Figure 9. The relationship between water withdrawal factors and capacity factors of the power plants.

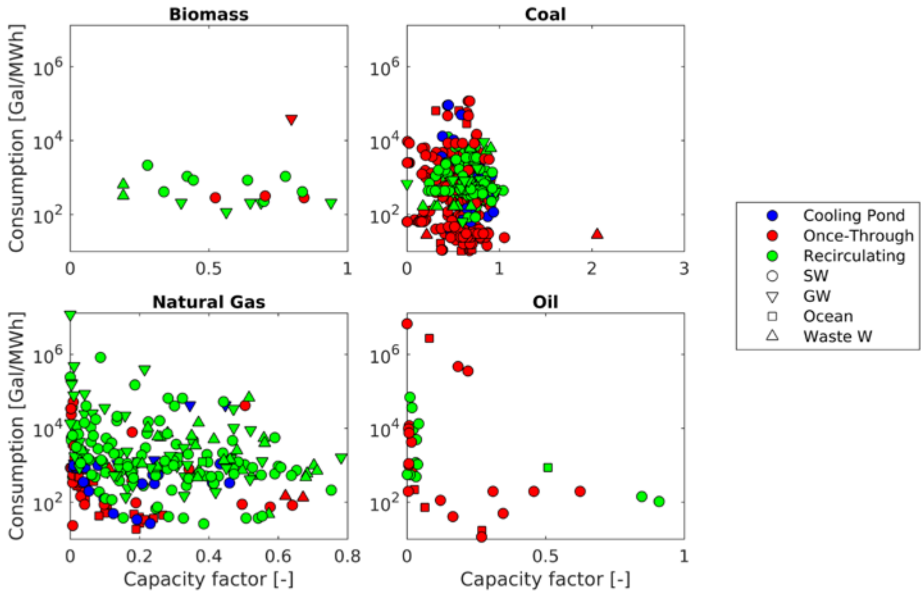

Figure 10. The relationship between water consumption factors and capacity factors of the power plants.

5 Significance

The study estimated the relationship between electricity load and temperature without prior assumptions about base temperatures or the slopes of electricity response. The empirically estimated base temperatures can serve as a reference for other future studies that wish to use CDDs and HDDs for load forecasting. The existence of a comfort zone indicates that the traditional assumption that the base temperatures are equal for CDDs and HDDs is inaccurate.

For other meteorological variables, the finding on the effect of past temperatures corroborates the findings of past studies, and the finding on wind speed shows it is relatively unimportant at the study regions. The finding on the effect of relative humidity is interesting because it suggests that effect of relative humidity is temperature-dependent, but cannot be modeled simply using an interaction term. While relative humidity is generally understood to induce higher electricity demand on hot days, the actual form of its relationship with electricity demand has not be well-studied. The results suggests a potential direction to be explored in future studies.

The study on water use of power plants is still in progress. Temporal-spatial statistical model of water withdrawal and consumptions factors are expected to be constructed based on multiple years of EIA Form 923 data. Monthly data is expected to be used. This will contribute to current literature by illustrating the seasonal and inter-annual evolution of the water use factors.

6 Publication Citations

Journal Articles:

Wang, Y., and Bielicki, J. (2016). "Investigating the Response of Hourly Electricity Load to Meteorological Variables using Lon-Term Data." *Applied Energy*. In preparation. Expected to be submitted in June 2016.

Presentations at Conferences:

Wang, Y., and Bielicki, J. (2015). "Extracting the Weather Response from Long-Term Hourly Electricity Load Data in an Eastern Region of the United States." *American Geophysical Union, Fall Meeting.* San Francisco, CA. December 14-18, 2015. Abstract GC51C-1102.

7 Number of Students Supported by the Project

This funding directly supported one Ph.D. student in the Environmental Science Graduate Program. An undergraduate student (B.S., Chemistry) also contributed to the project with data that she collected during an independent study course (ENVENG 4998).

8 Professional Placement of Graduates

The Ph.D. student who was funded by this grant and conducted this work will take her Ph.D. qualifying exams during the summer of 2016. Her exam will be based in part on the work that was conducted with this funding. The B.S. student who contributed to this project, but was not funded by it, has taken a position with the Sierra Club, based in part on her experience with this project.

9 Awards or Achievements

None (yet)

10 Additional Funding

Research initiated by this grant is continuing under an existing grant from the U.S. National Science Foundation on Sustainable Energy Pathways. Follow-on funding has not yet been procured, but discussions are underway with AEP and lessons learned from this one-year project have been incorporated into a proposal to the U.S. National Science Foundation and will be a part of a proposal that is expected to be submitted to the U.S.D.A.