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Data Analytics for Evaluating Campus Energy Use

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Data Analytics for Analyzing Campus Energy Use

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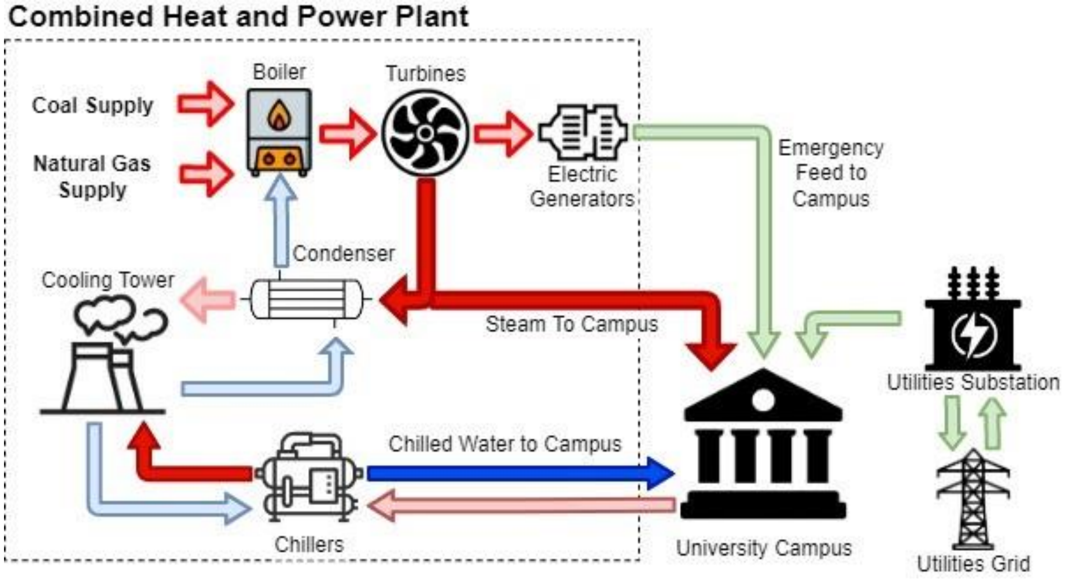
AeL Applied Energy Laboratory

Introduction

- Cogeneration plant supplies utilities to campus
- Chilled Water
- Steam
- Electricity
- Domestic Water



Problem

- Production and energy distribution metered at CHP plant and at buildings
- Data recorded every 5 – 60 seconds
- Improvements in how data is used can result in more efficient asset management and improve demand prediction

Methodology

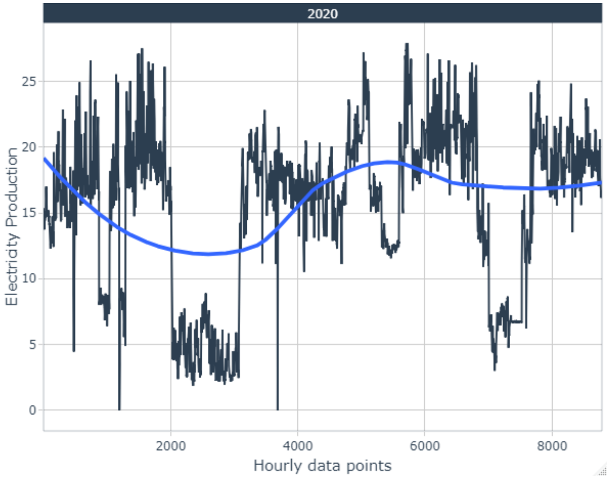
- Bayesian multilevel additive modeling used to analyze significant variables and their impacts on supply and demand
- Population and group effects considered
- Data Collection
- R Programming Language
- Predictor and response variables
- Trending relationships
- Predictive modeling

$$y_{i,j} = \sum_{j=1}^{J} \alpha_j u_j + \sum_{k=1}^{K} \beta_k x_{ij,k} + \sum_{q=1}^{Q} f_q(z_{ij,q}) + \varepsilon_{ij}$$

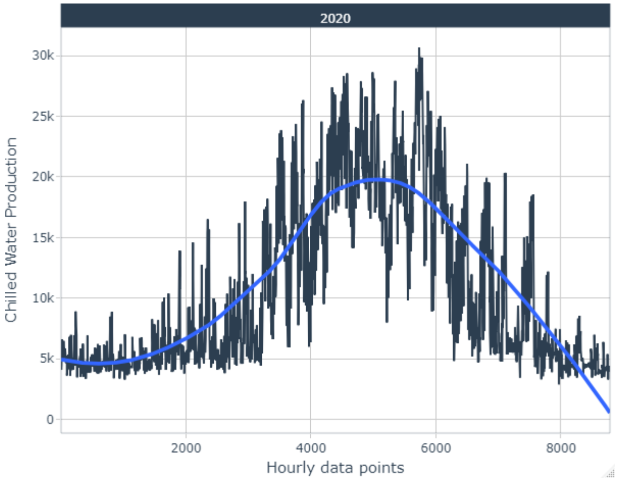
Data Collection

- Data collected from 2018 to 2021
- 1 hour averages

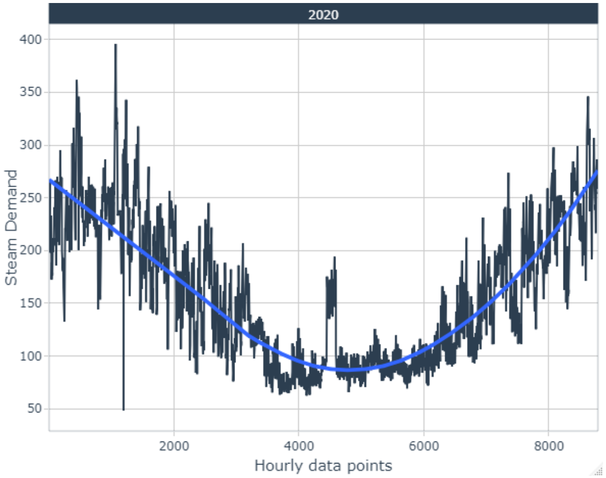
(a) 2020 Electricity Production



(b) 2020 Chilled Water Production



(c) 2020 Steam Demand



Variable Definitions

Demand- The energy required by all campus buildings

Production- The energy generated at the CHP plant

Linear Effects – variables with a direct correlation to the response variables

Non-Linear Effects – variables with a lower order impact on the response variables

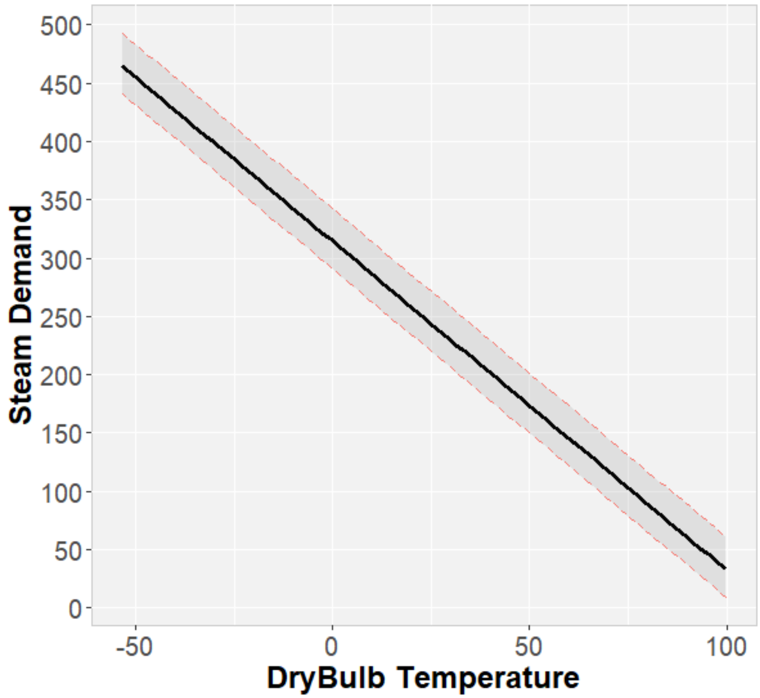
Group Effects – variables that impact all response variables

Relationships Between Variables

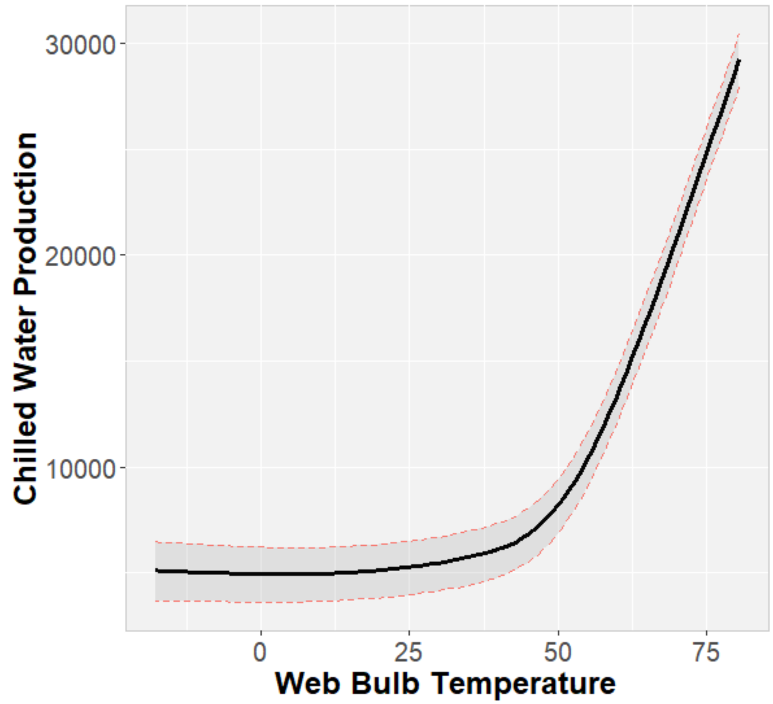
<table>
<tr><th colspan="2">Response variables / Predictor variables</th><th>Linear population effects</th><th>Non-linear population effects</th><th>Group effects</th></tr>
<tr><td rowspan="3">1. Demand (Building)</td><td>Steam</td><td>•Dry bulb air temperature</td><td>NA</td><td rowspan="7">•Campus size (gsf or gsm)
•Time of Day (ToD)
•Month</td></tr>
<tr><td>Domestic Water</td><td>•Dry bulb air temperature</td><td>NA</td></tr>
<tr><td>Electricity</td><td>•Wet bulb temperature</td><td>NA</td></tr>
<tr><td rowspan="3">2. Production (CHP)</td><td>Steam</td><td>•Steam use (building)
•Electricity use (building)</td><td>•Dry bulb air temperature</td></tr>
<tr><td>Chilled Water</td><td>NA</td><td>•Wet bulb temperature
•Domestic Water</td></tr>
<tr><td>Electricity</td><td>•Steam use (building)
•Electricity use (building)</td><td>•Dry bulb air temperature</td></tr>
<tr><td colspan="2">3. Electricity Purchase</td><td>•Steam demand (building)
•Electricity demand (building)
•Electricity production
•Chilled water production</td><td>NA</td></tr>
</table>

Steam and Chilled Water Data

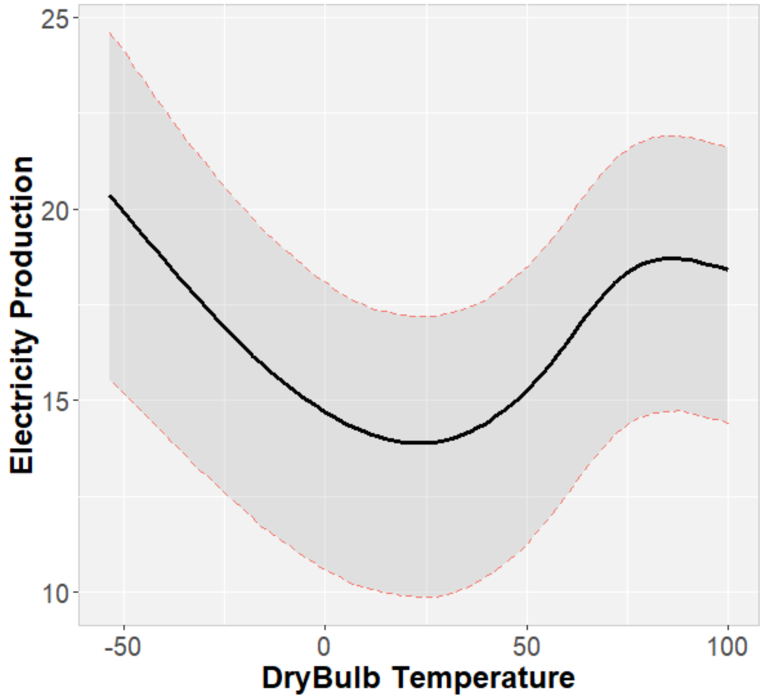
(a) Steam Demand vs. Dry Bulb Temp.



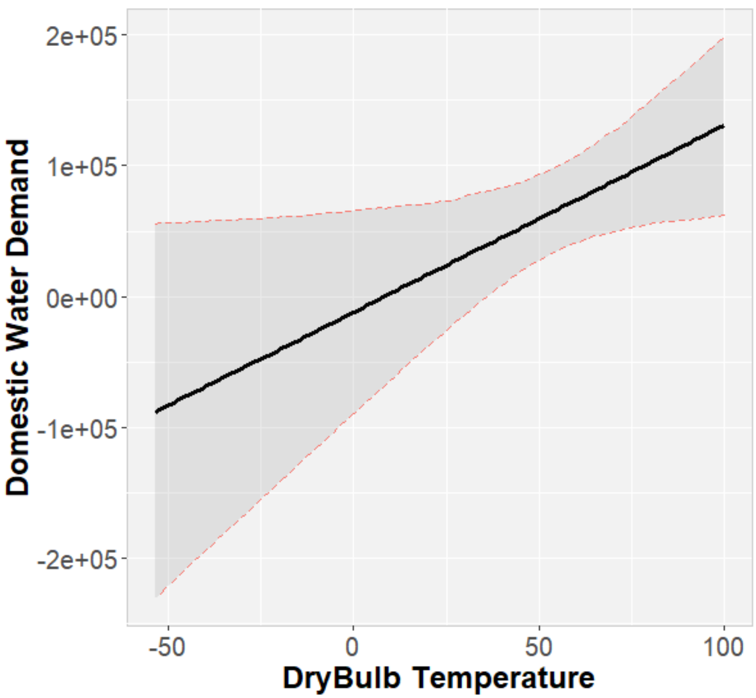
(b) Chilled Water Production vs. Wet Bulb Temp.



(c) Electricity Production vs. Dry Bulb Temp.



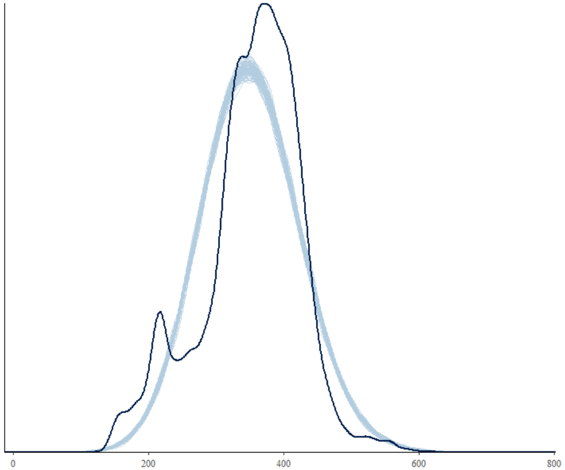
(d) Domestic Water vs. Dry Bulb Temp.



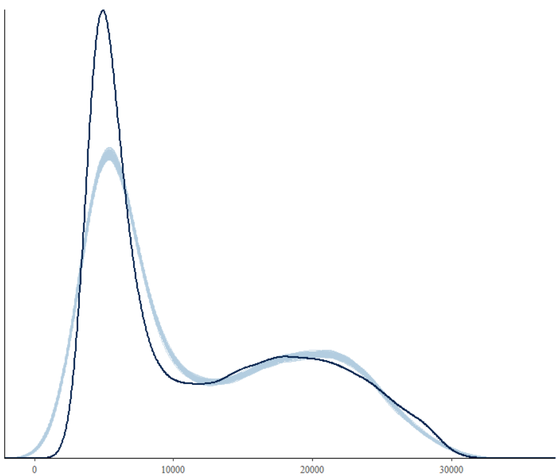
Posterior Predictive Checking

- ❑ Output of predictive model compared to observed data

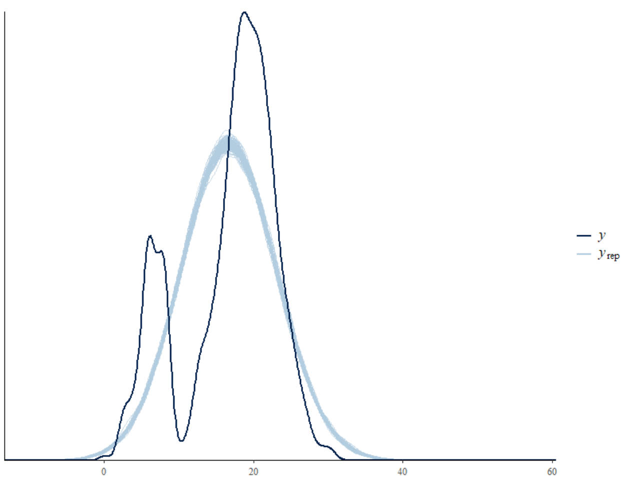
(a) Steam Production



(b) Chilled Water Production

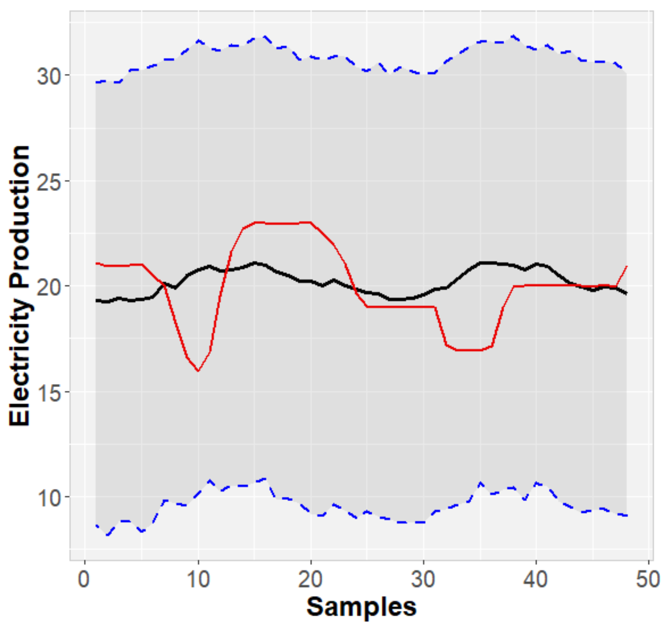


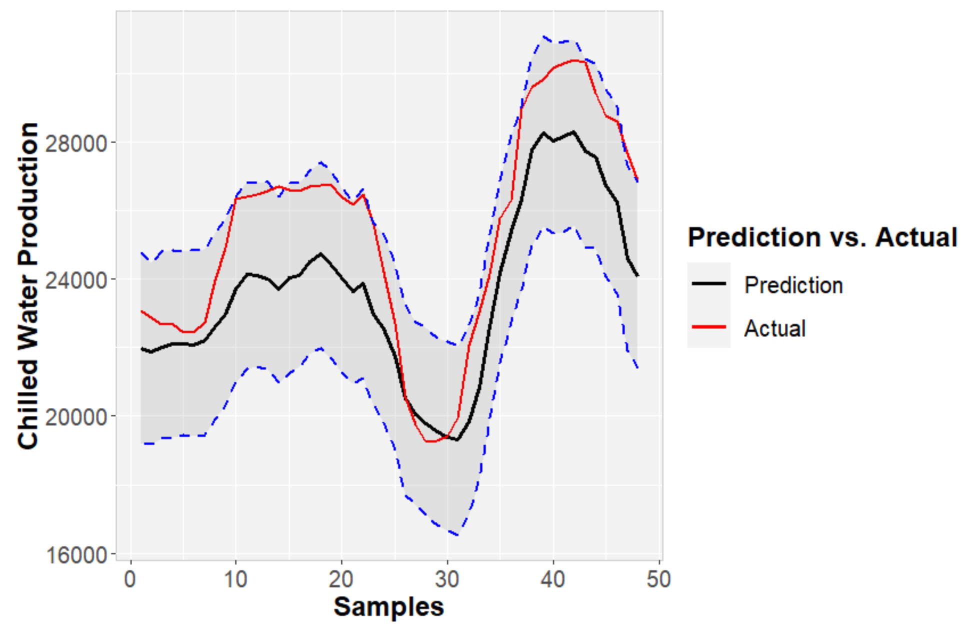
(c) Electricity Generation



Predictions

- Sampled data points compared to outputs from models
- Within 95% confidence interval





Conclusions

- Bayesian models are useful for identifying the relationship between variables such as air temperature and energy demand
- Models can be used to predict energy demand based on conditions such as weather forecasts
- The accuracy of models can be further improved through exploration of additional predictor variables

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