Integrating Data Science Methods and Life Cycle Assessment (LCA): Application to the Power Sector

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Presentation

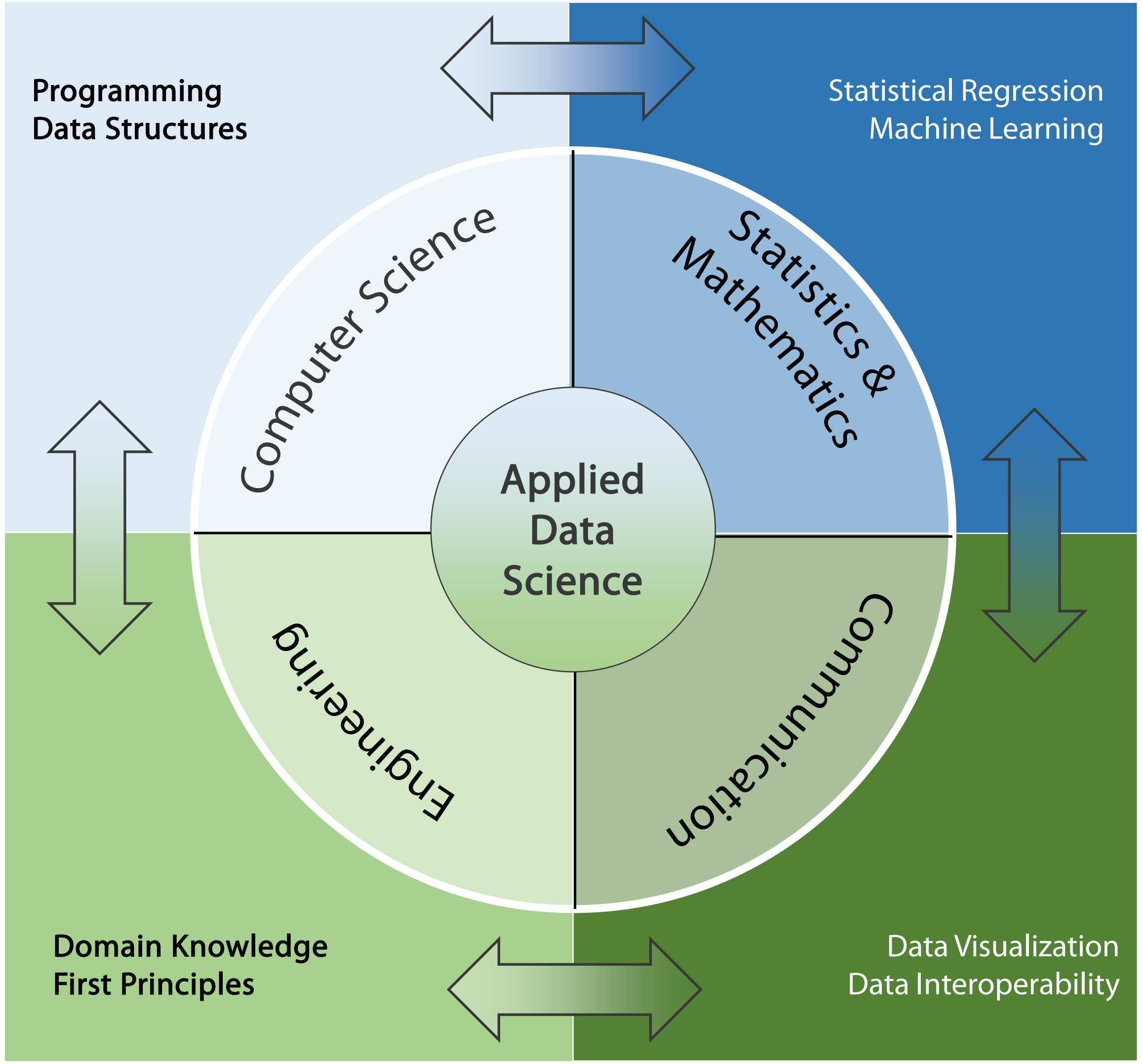
Outline

- **Introduction**
  - Data Science and LCA
- **Power Sector Case Studies**
  - Natural Gas Liquids Unloading
  - U.S. Hydropower
  - U.S. Coal and Natural Gas Fleet
- **Conclusions**

Introduction

Applied Data Science

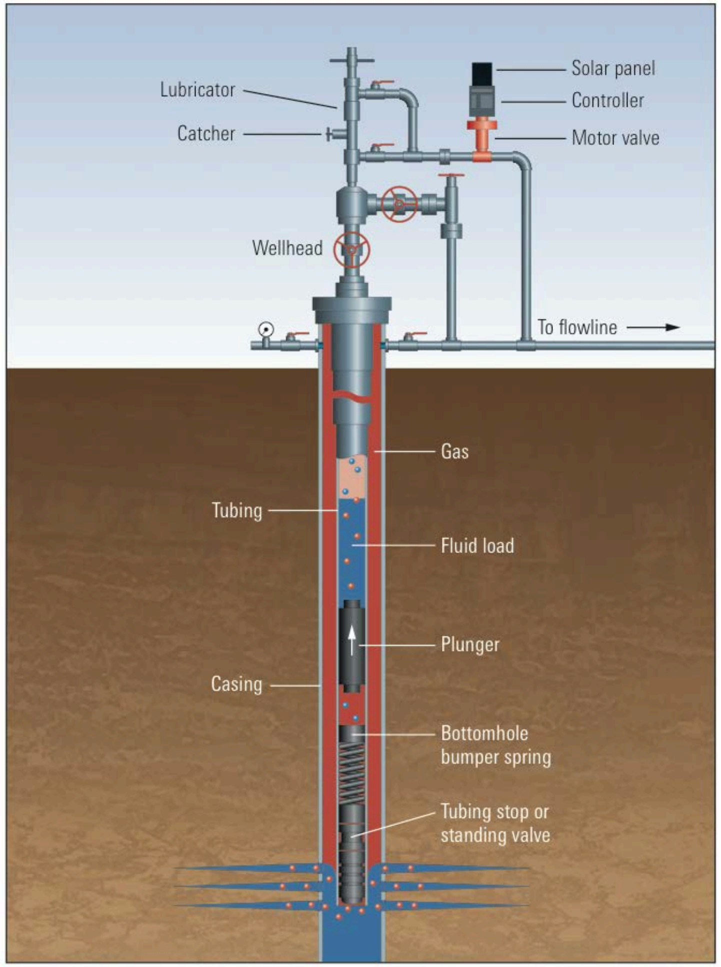
- **Applied Data Science**
  - Multidisciplinary field for knowledge generation and synthesis of structured and unstructured data
- **Complimentary to LCA**
  - Data-Driven Approach
  - Large-Scale Datasets



Natural Gas Liquids Unloading

Introduction

- **Research Objectives**
  - Develop a probabilistic 'bottom-up' framework to quantify methane emissions from natural gas liquids unloading
  - Utilize engineering design equations and first principles to characterize methane emissions from liquids unloading activities and account for component-level and regional variability



Plunger Lift Schematic[1]

[1]Schlumberger, Plunger Lift. *Oilfield Review* 2016, *The Defining Series*

Natural Gas Liquids Unloading

Engineering Design Equations

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- **Multivariable Equations**
  - Venting Frequency
  - Casing/Tube Diameter
  - Well Depth
  - Shut in Pressure
  - Standard Flow Rate
  - Venting Duration
- **Non-Plunger Systems**
  - Equation W-8 from 40 CFR 98 Subpart W
- **Plunger Systems**
  - Equation W-9 from 40 CFR 98 Subpart W

Casing Diameter

Venting Frequency

Shut in Pressure

Binary Variable

$$E_{s,p} = \sum_{p=1}^{w}\left[V_p \times \left(\underbrace{(0.37 \times 10^{-3})}_{\text{Unit Conversion}} \times CD_p^2 \times WD_p \times SP_p\right) + \sum_{q=1}^{V_p}\left(SFR_q \times \left(HR_{p,q} - 1.0\right) \times Z_{p,q}\right)\right]$$

Well Depth

Venting Duration

Standard Flow Rate

W-8: Non-Plunger Systems

Tubing Diameter

Venting Frequency

Shut in Pressure

Binary Variable

$$E_{s,p} = \sum_{p=1}^{w}\left[V_p \times \left(\underbrace{(0.37 \times 10^{-3})}_{\text{Unit Conversion}} \times TD_p^2 \times WD_p \times SP_p\right) + \sum_{q=1}^{V_p}\left(SFR_q \times \left(HR_{p,q} - 0.5\right) \times Z_{p,q}\right)\right]$$

Well Depth

Venting Duration

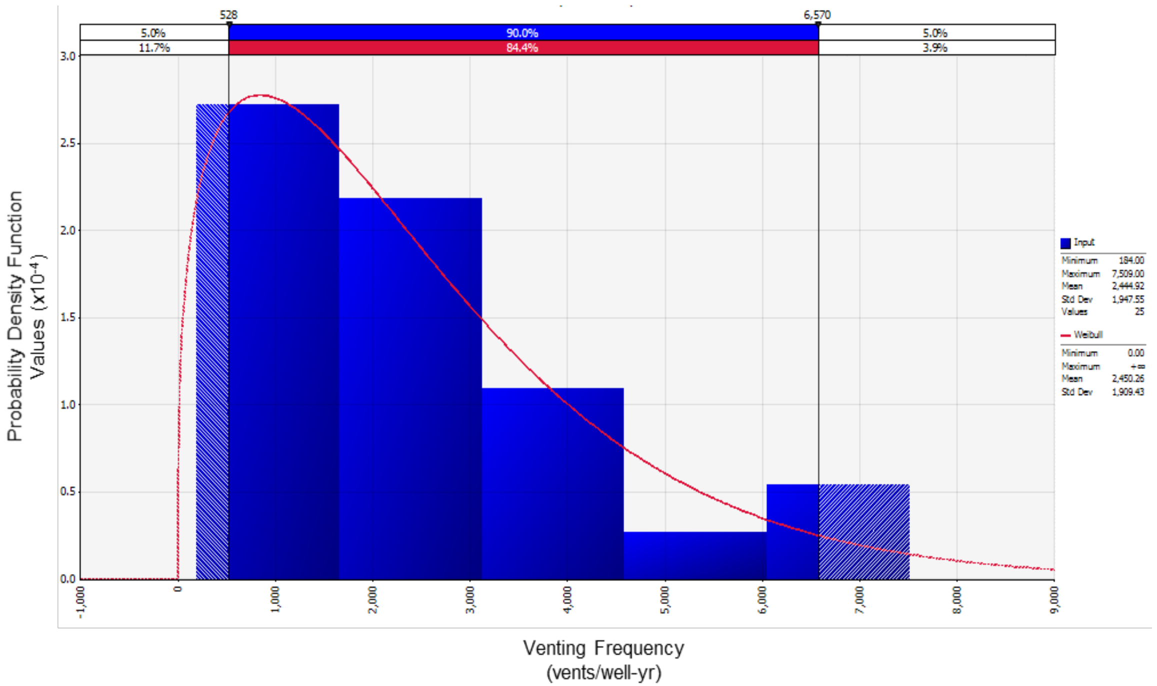
Standard Flow Rate

W-9: Plunger Lift Systems

Natural Gas Liquids Unloading

Probability Distributions and Monte-Carlo Simulation

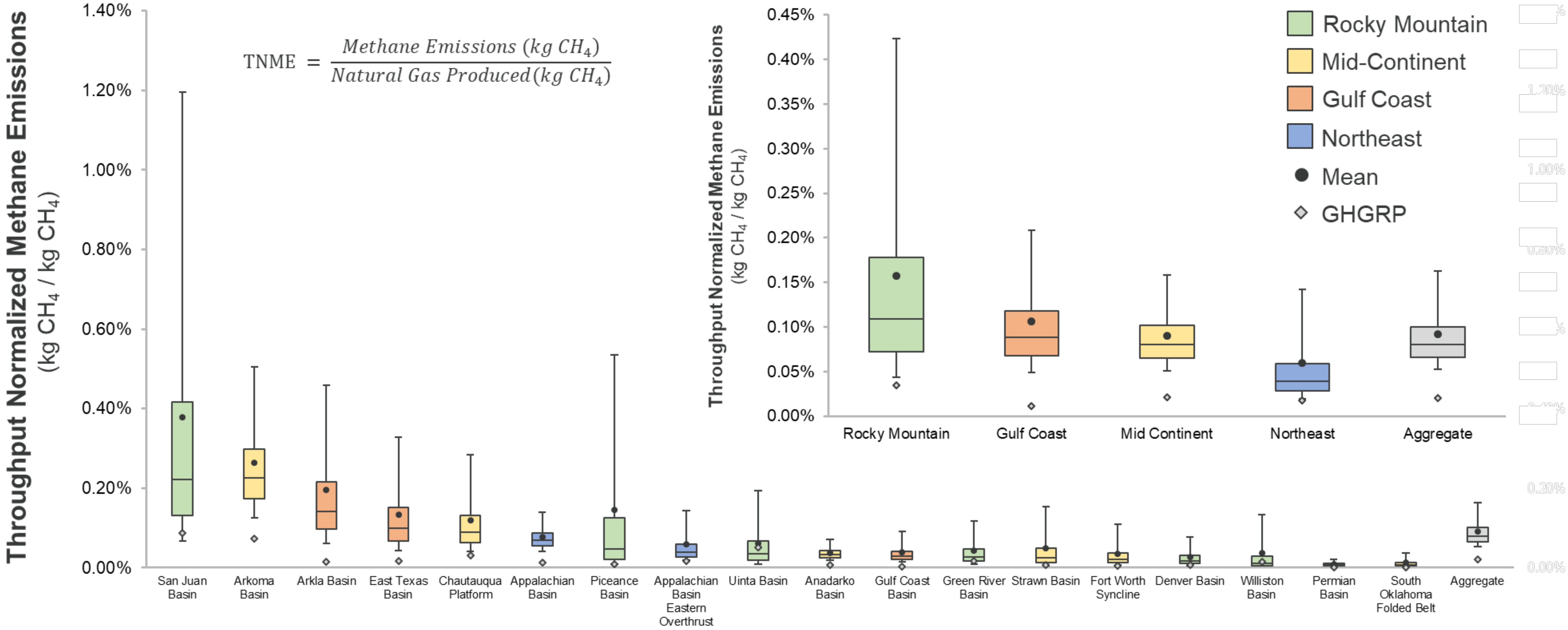
- **Develop Probability Distributions for Key Parameters**
  - Several Heuristics
    - Goodness of Fit Criteria
    - Precedence in the literature
    - Distribution is physically relevant
- **Monte Carlo Simulation**
    - Randomly sample from probability distributions (10,000 trials)



Simulated Liquids Unloading Venting Frequency (vents/well-year), Automatic Plunger-Lift

Natural Gas Liquids Unloading

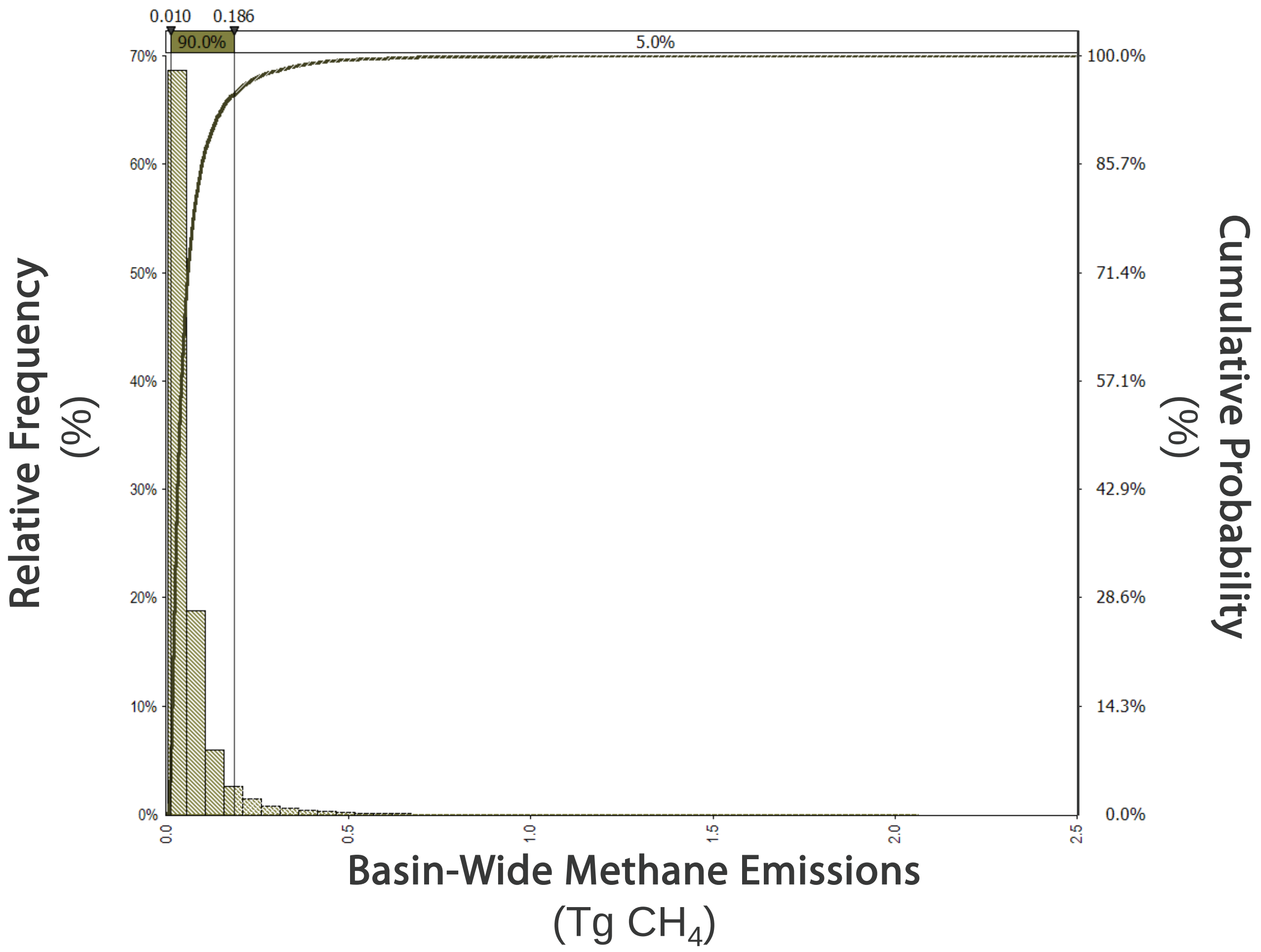
Throughput Normalized Methane Emissions (TNME)



Natural Gas Liquids Unloading

San Juan Basin

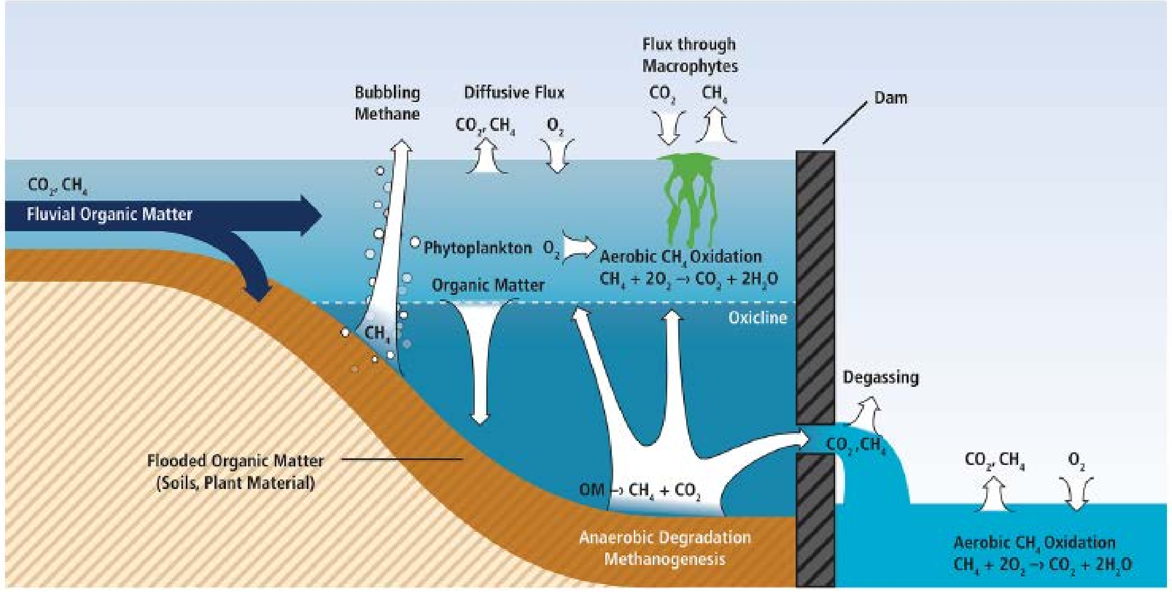
- **Methane emissions from the San Juan basin exhibit a heavy-tail distribution**
  - Simulated emissions are highly skewed, with a small portion of natural gas activities responsible for a disproportionately large fraction of total emissions
  - The high number of venting automatic plunger-lift wells and the skewed emissions distribution from automatic-plunger systems drives the heavy tail distribution



U.S. Fleet Hydropower

Introduction

- **Primary Research Objectives**
  - Evaluate the environmental impacts from U.S. hydropower in 2016, with specific focus on GHG emissions and Water Footprint
  - To the extent possible use publicly available datasets and open-source platforms



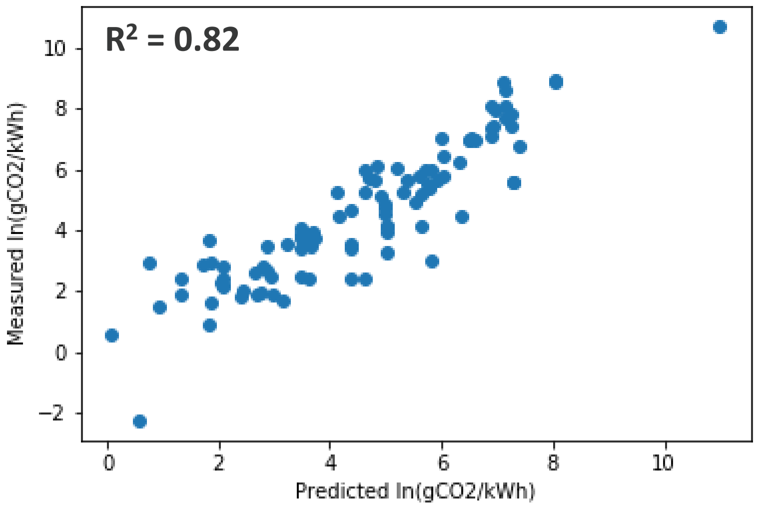
Possible pathways for biogenic methane and carbon dioxide emissions from hydropower stations.

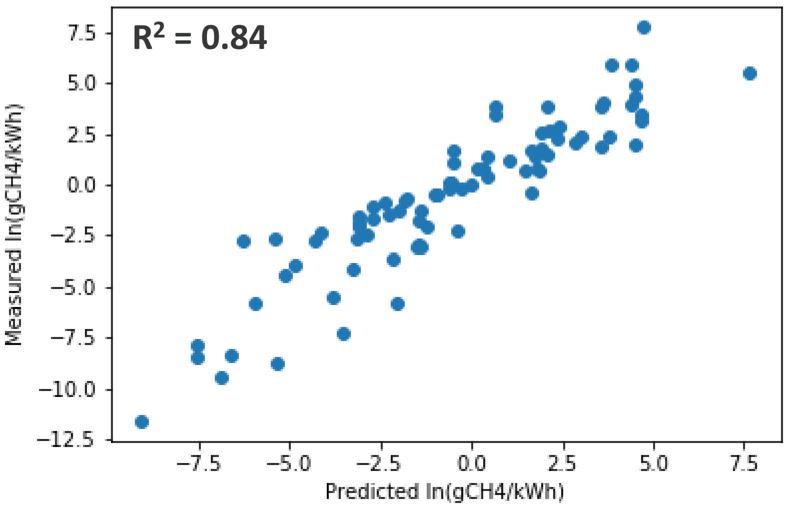
***Source**: IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation

U.S. Fleet Hydropower

Statistical Regression

- **Regression**
  - Training dataset via Scherer et al. 2016
    - *Dependent Variables*: ln(gCO_2 kWh^{-1}), ln(gCH_4 kWh^{-1})
    - *Predictors*: ln(ATE), ln(Area), ln(Age), ATE, Area, Age, Tmax, Tmean, Tmin, Longitude, Latitude, NPP
  - RFECV used for feature selection
    - Feature ranking with recursive feature elimination and cross-validated selection of the best number of features, based on python's scikit-learn machine learning API
  - LassoCV Regression
    - Lasso linear model with iterative fitting along a regularization path, the best model is selected by cross-validation





U.S. Fleet Hydropower

Climatological Data

- **Climate Data**
  - NOAA Global Summary of the Month accessed via FTP
    - Pan Evaporation, Tmax, Tmin, Station Lat/Long for 2016
    - Evap: 200 Stations
    - Tmax: 13,532 Stations
    - Tmin: 12,923 Stations
- **Inverse Distance Weighting**
  - Interpolate climate data to determine climatic conditions at hydropower reservoirs

U.S. Fleet Hydropower

Allocation Schemes

- **Allocation Schemes**
  - Primary Purpose
    - Allocates environmental burdens to the primary purpose of the dam
  - Rank-based
    - Allocates environmental burdens based on the ranking of the dam's purposes/functions
  - Equitably
    - Allocates environmental burdens equitably across all of the dam's purposes/functions
  - Economic Allocation
    - Allocates environmental burdens based on the economic value of hydropower relative to the dam's other purposes/functions
    - Based on data reported by ORNL*, and contingent on installed capacity and number of dam functions

Rank-Based Allocation

$$f_A = \frac{n + 1 - \text{ranking}}{\sum_{i=1}^{n} i}$$

Economic Allocation

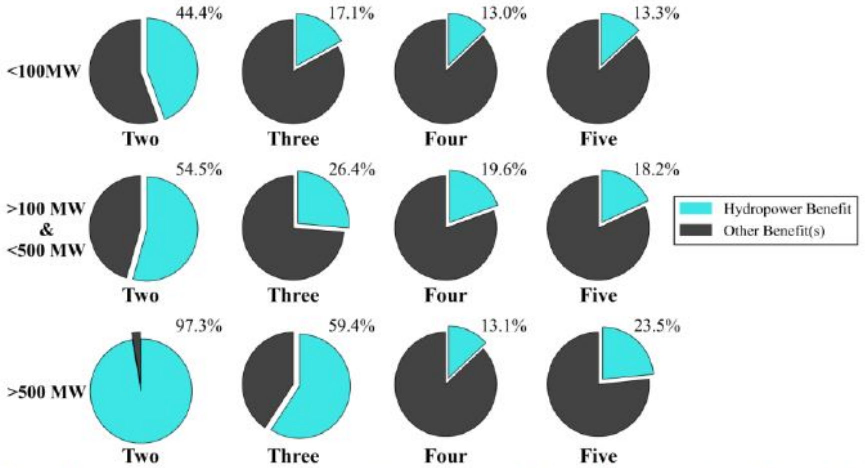


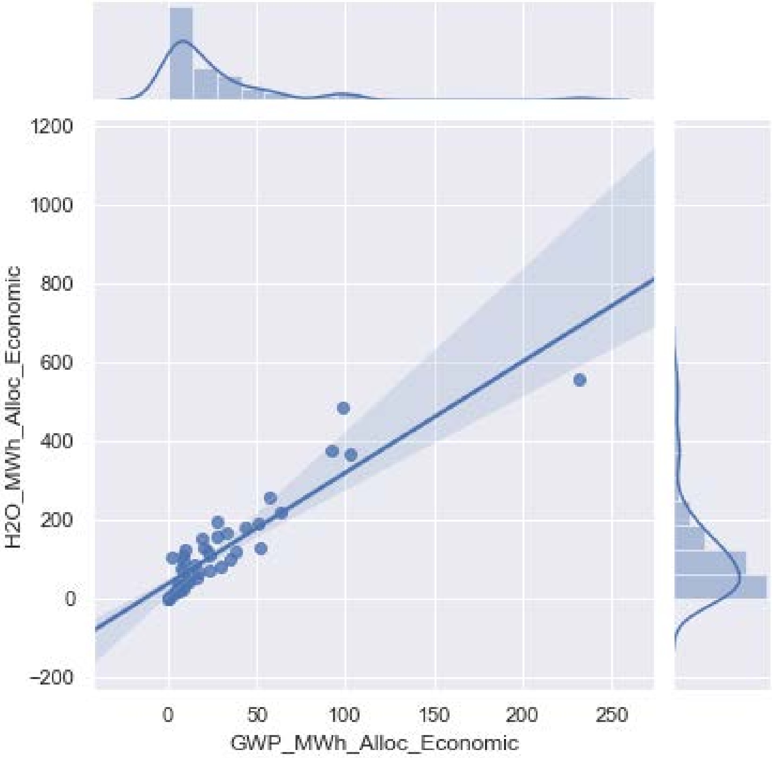
Figure 5 - *Average percentage of power benefit per reservoir. Columns depict the number of quantifiable purposes, while rows represent a range of installed capacity.*

*Source: The economic benefits of multipurpose reservoirs in the United States – federal hydropower fleet (2015)

U.S. Fleet Hydropower

Results and Discussion

Allocation Schemes	No Allocation	Primary Purpose (F)	Primary Purpose (L)	Equitable	Rank (F)	Rank (L)	Economic
GWP (kg CO2e / MWh)	47.09	18.75	16.63	14.01	20.10	18.43	12.32
H2O (m3 H2O / MWh)	176.82	76.25	66.72	54.97	78.29	70.44	50.90

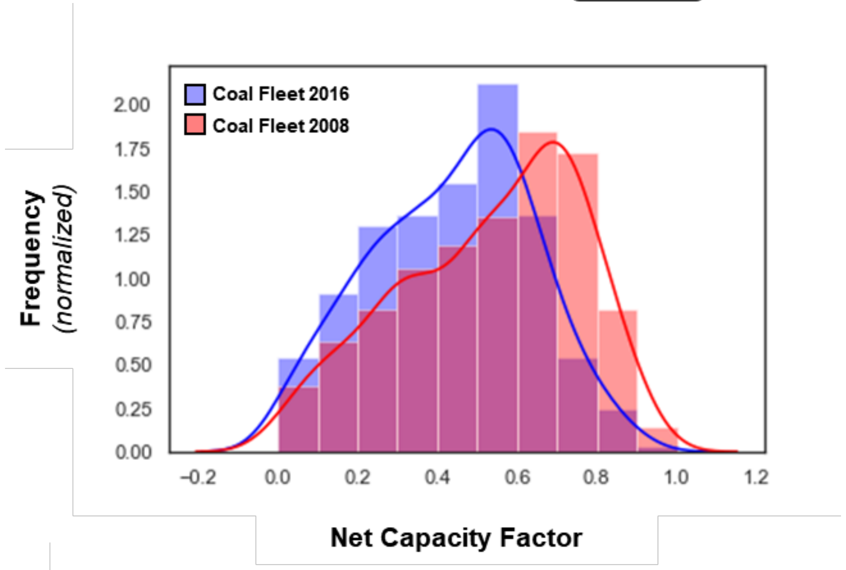


- **Allocation Schemes**
  - Significant impact on the environmental profile of hydroelectricity
- **Regional Variability**
  - Statewide differences in hydroelectric power GWP and water intensity

U.S. Fossil Power Fleet

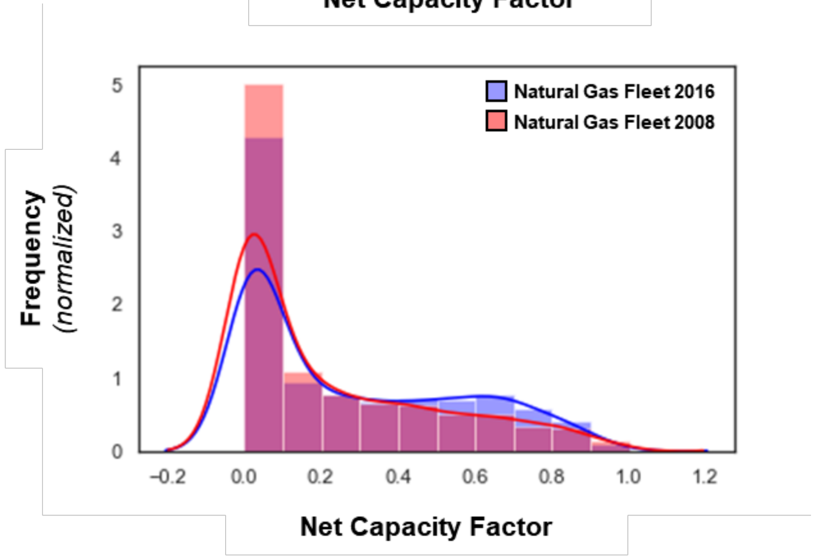
Introduction

Thesis: Shifting operational modes of thermal power plants as a response to external factors such as an increasing penetration of variable and/or intermittent power generation technologies may result in unintended and/or higher relative emissions rates



Research Questions:

1. Have historically baseload assets changed their mode of operations over the past decade?
2. How do the emissions profiles of baseload assets change across modes of operations?
3. Evaluate the time-evolution emissions intensity of the fossil fleet



This work was made possible by funding provided by the Electric Power Research Institute (EPRI)

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Time Series Evolution of Fossil Fleet

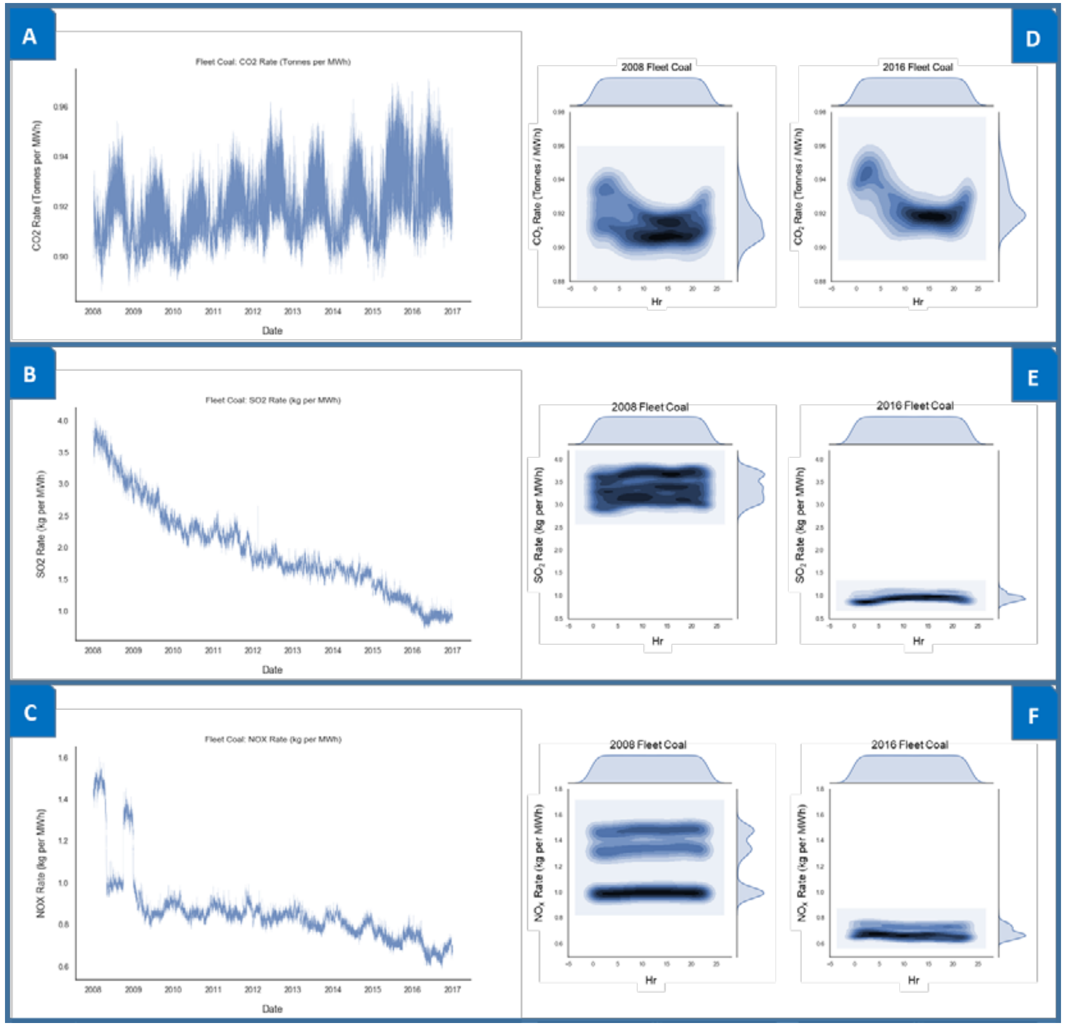
Data Sources

- **Model Development**
  - Python
- **Key Data Sources:**
  - EPA's Continuous Emissions Monitoring System (CEMS)
    - Hourly emissions data for CO_2, SO_2, and NO_X
    - Heat Input
    - Gross Generation
  - EIA 923 and EIA 860
    - Net Generation
    - Generator nameplate capacity

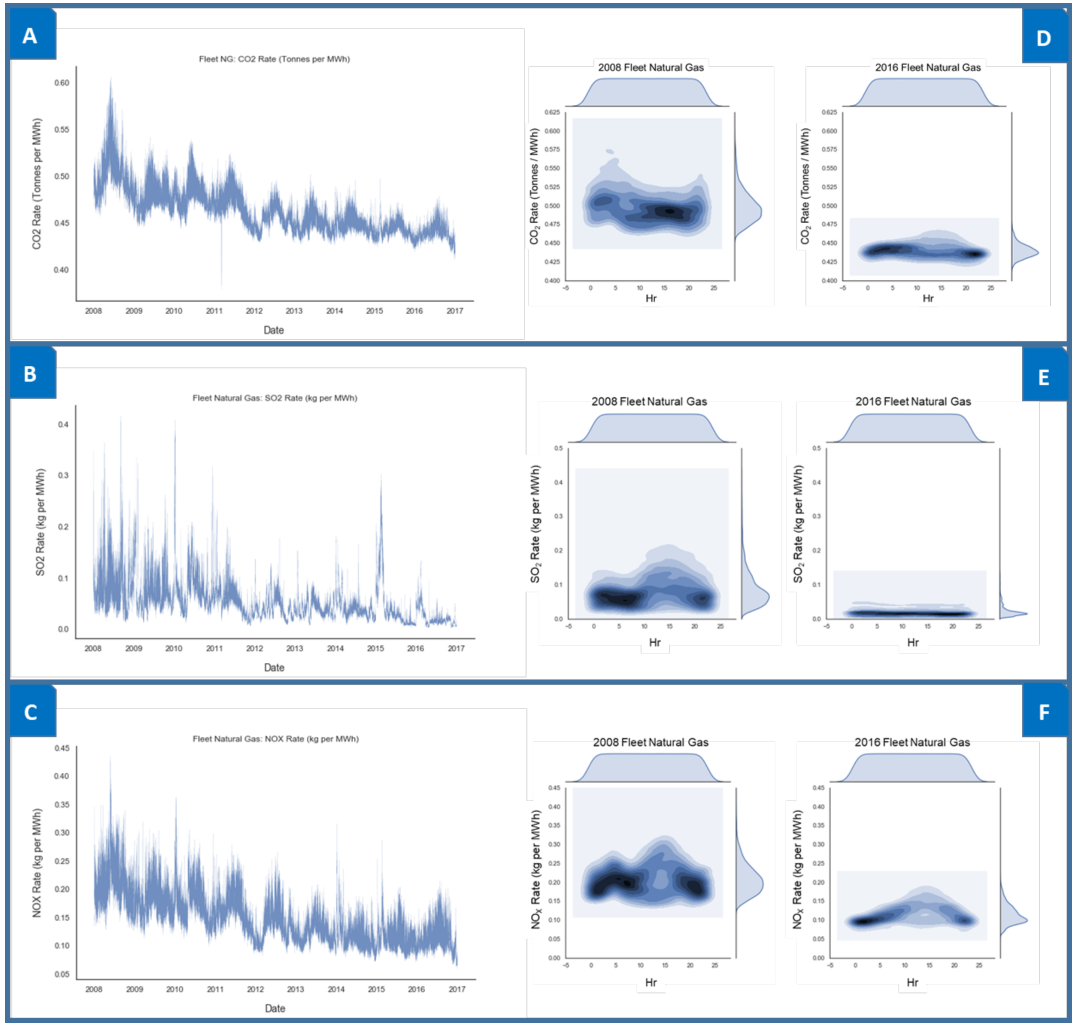
U.S. Fossil Power Fleet

Fossil Fleet, Emissions Rates

Time Series: Coal Fleet



Time Series: Natural Gas Fleet



EPRI (2019). Evaluation of Emissions Profiles for Electric Generating Units as Generation Shifts From Baseload to Should/Peaking: Trends in fleet coal and natural gas across the 2008 to 2016 timeframe. Electric Power Research Institute. Report in preparation.

U.S. Fossil Power Fleet

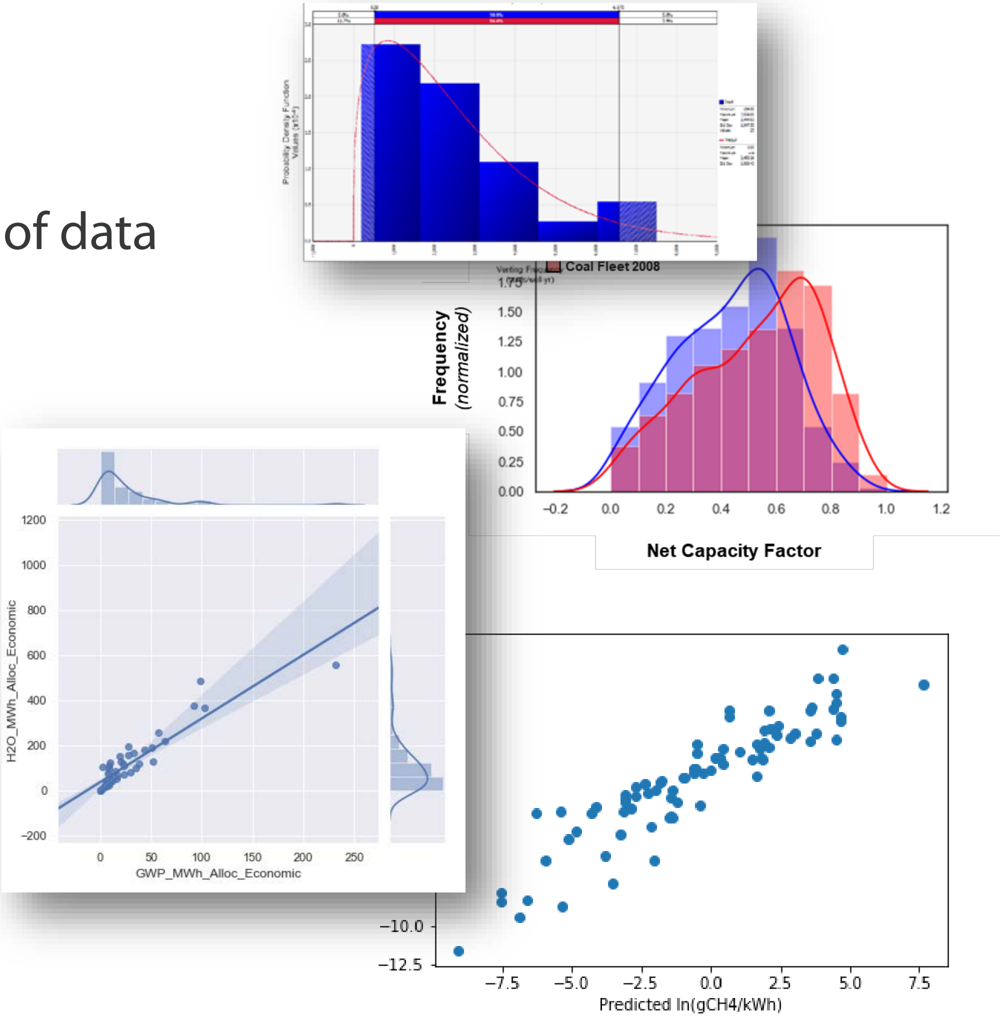
Key Findings

- **Baseload Power**
  - In 2016, natural gas displaced coal as the primary source of 'baseload' net generation, constituting 51% of cumulative fossil baseload net generation.
- **Coal Fleet**
  - Significant operational changes between 2008 and 2016 has contributed to lower coal fleet efficiency and higher CO_2 emissions rates. Dramatic reduction in SO_2 and NO_X emissions rates driven by the implementation of emissions control technologies to comply with EPA regulations.
- **Natural Gas Fleet**
  - Dramatic increase in fleet gross generation, installed capacity, and fleet efficiency, resulting in lower CO_2 and SO_2 emissions rates over the 2008 to 2016 time period. Significant reduction in NO_X emissions rates driven by efficiency improvements and implementation of emissions control technologies

Summary

Conclusions

- **Intersection of Data Science & LCA**
  - Several case studies in the Energy Sector
    - Enhanced knowledge generation and synthesis of data
    - Methods have cross-sector applicability
- **Value addition**
  - Statistical analysis
  - Visualization
  - Data/Database management
  - Reproducibility
  - Open Source Platforms



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