GTI ENERGY SAGE

STATISTICS, ANALYTICS, AND GIS IN ENERGY CONFERENCE

Predicting the Impact of Storms on Utility Customers Using Weather Analytics

David J Corliss, PhD
DTE Energy

August 14, 2025

DTE Energy

SAGE

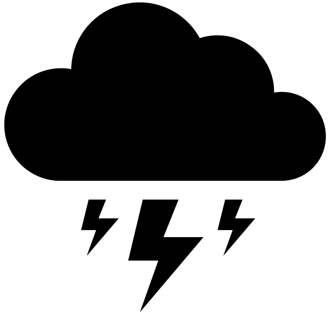
Predicting the Impact of Storms on Utility Customers Using Weather Analytics

With a PhD in statistical astrophysics, David J Corliss, PhD is a Senior Data Scientist at DTE Energy, an electric and gas utility based in Detroit, MI. He is active in the American Statistical Association, where he serves on the Board of Directors, writes a monthly column in Amstat News on data for social good, and teaches courses on ethical best practices in data, analytics, and AI. Dr. Corliss is the founder of Peace-Work, a volunteer cooperative of statisticians, data scientists and other researchers applying analytics in issue-driven advocacy.

Outline

- Introduction: Weather Analytics
- Physics-Informed Artificial Intelligence
- Weather Analytics: Challenges and Considerations
- Weather Analytics: Methods and Algorithms
- Conclusions

Introduction: Weather Analytics



DTE Energy Weather Analytics Model: Project Goal

Deliver a product that can provide predictability on a regional approach so that DTE can resolve outage issues and apply resources where needed in a cost-effective way

Outage Predictability

Hourly prediction of events by Service Center

Identify Areas of Greatest Impact

Regional damage multiplier prediction

Resource Management

Predict number of resources needed

DTE Energy

SAGE

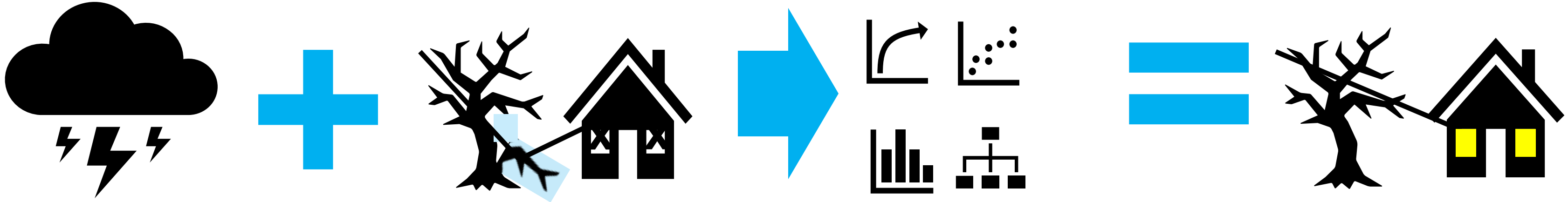
DTE Weather Analytics Model: Concept Flow Chart

Leverage Publicly Available High Quality Weather Forecast Data from NOAA

Match to DTE Outage History

Apply Multiple Modeling Methods

Local Outage Predictions by Day

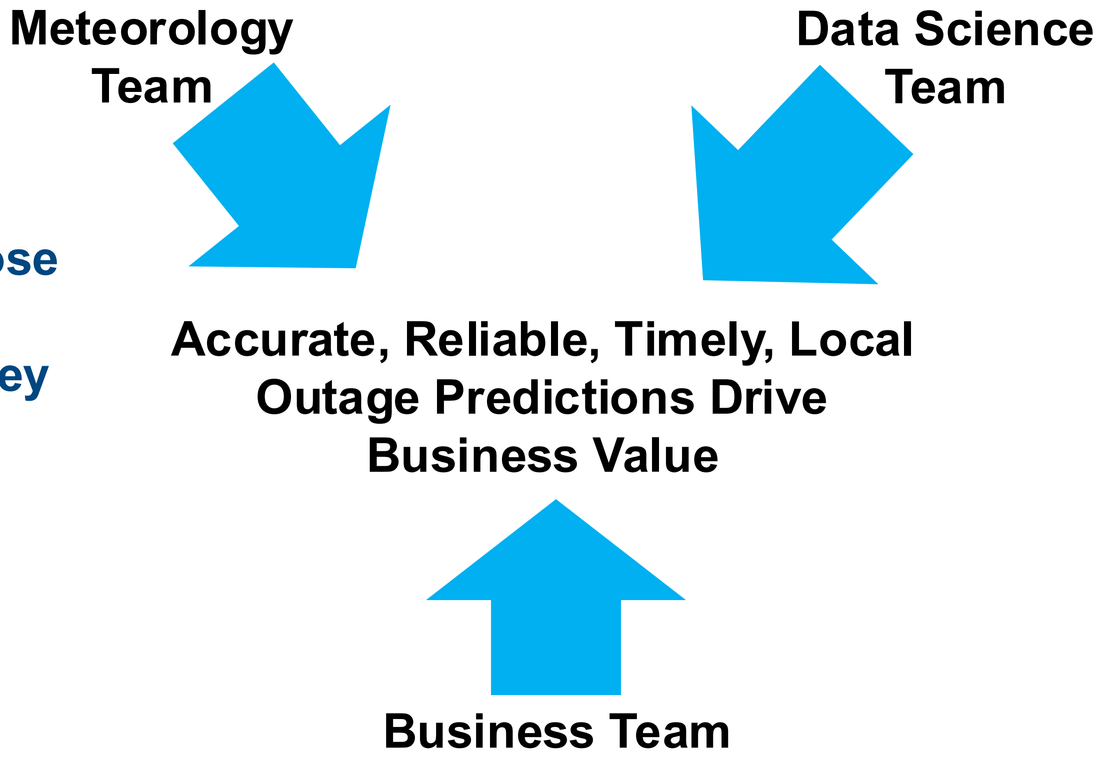


DTE Energy

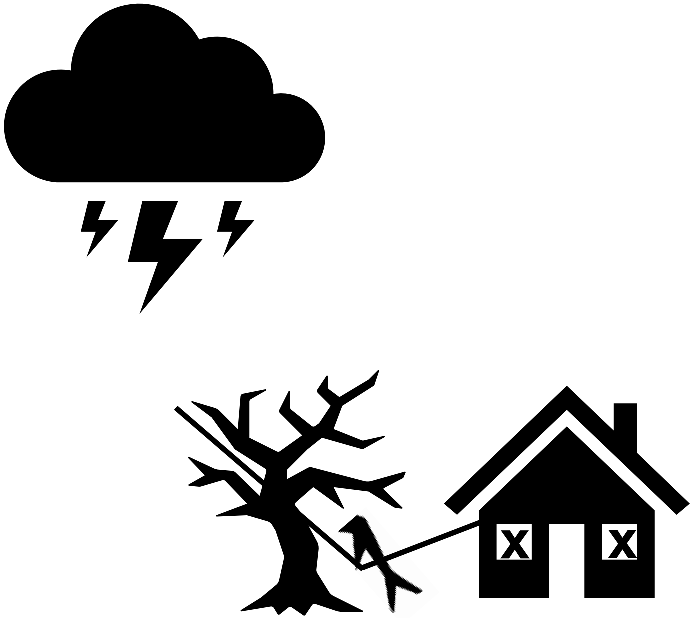
SAGE

DTE Weather Analytics Model: Business Model

Everything depends on a close partnership between three key stakeholders



Physics-Informed Artificial Intelligence



Physics-Informed AI

The integration of the principles, equations, and constraints of physical science to inform decision science, increase accuracy, and optimize processes and results.

- Application of atmospheric physics in weather forecasting algorithms
- Analysis of the equations of motion as system constraints
- Inclusion of energy transfer mechanisms in AI describing physical processes
- Estimating system and algorithm performance characteristics based on physical limitations

Physics-Driven Features in Weather Impact Analytics

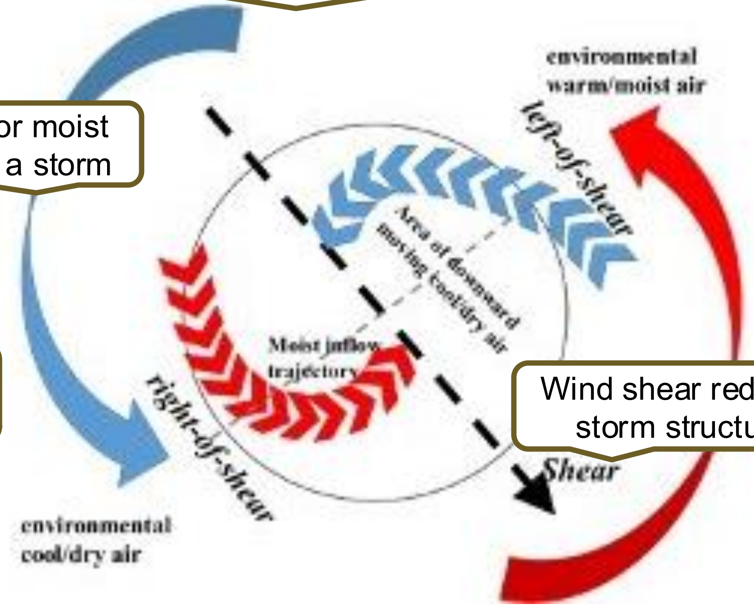
C

Temperature Differential: Cold fronts generate stronger thunderstorms

H

Humidity: Dry or moist air moving into a storm

Weather patterns often last for several days then change => LSTM



Capping: stable air layers aloft hinder storm development

Wind shear reduces storm structure

Energy flow from warm air moving into a storm

Drawing: Wadler, J. et al., AOML Communications / NOAA 2022

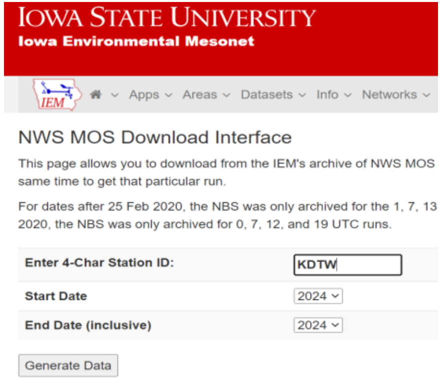
DTE Energy

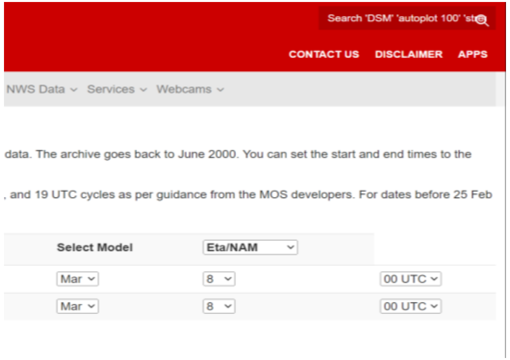
SAGE

Weather Analytics: Challenges and Considerations

Challenges and Considerations: Available Data

Data: ISU Weather Forecast Archive



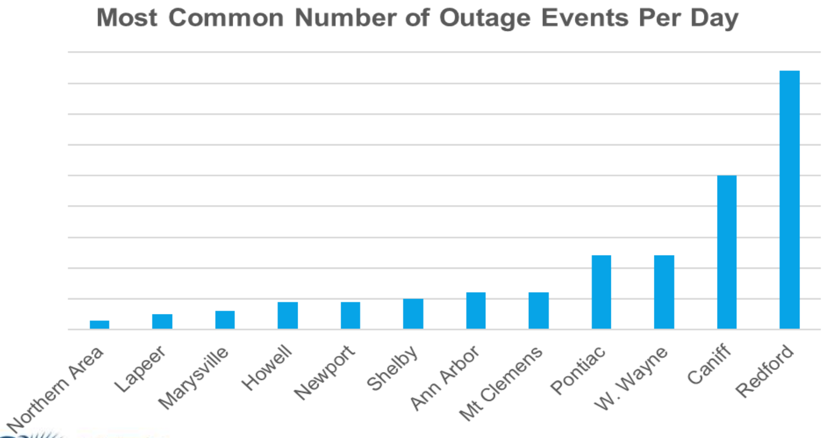


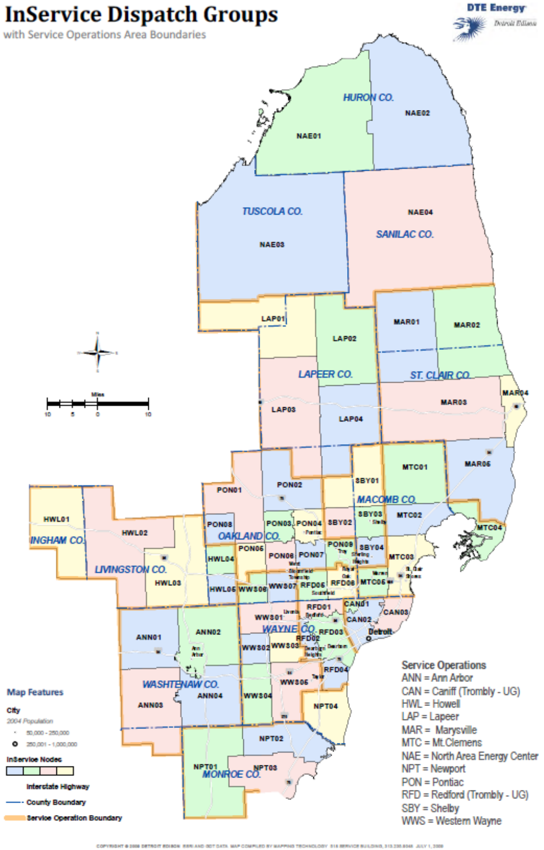
Available Data	
Max/Min Temp [F]	Freezing Rain Probability [%]
2m Air Temperature [F]	Snowfall Probability [%]
2m Dew Point [F]	Precipitation Type
Cloud Coverage	Sky Coverage [%]
10m Wind Direction [deg]	Wind Gust [kts]
10m Wind Speed [kts]	3 Hr Thunderstorm Prob [%]
6 Hr Probability of Precipitation [%]	Probability Freezing Rain [%]
12 Hr Probability of Precipitation [%]	Probability of Snow [%]
6 Hr Quantitative Precip Forecast	Probability of PL [%]
12 Hr Quantitative Precip Forecast	Probability of Rain [%]
6 Hr Thunderstorm Probability [%]	0-6 km Vertical Wind Shear
12 Hr Thunderstorm Probability [%]	Snow Level
Categorical Snow	I06
Categorical Ceiling Height	Lowest Cloud Base
Categorical Visibility	Significant Wave Height
Obstruction to Vision	

Challenges and Considerations: Geography

Top Factors Driving Regional Differences

- Number of customers in each area
- Local differences in the severity of weather events
- Close to the lakes vs. inland
- Seasonal changes have different timing
- Land use - buildings vs houses vs farms



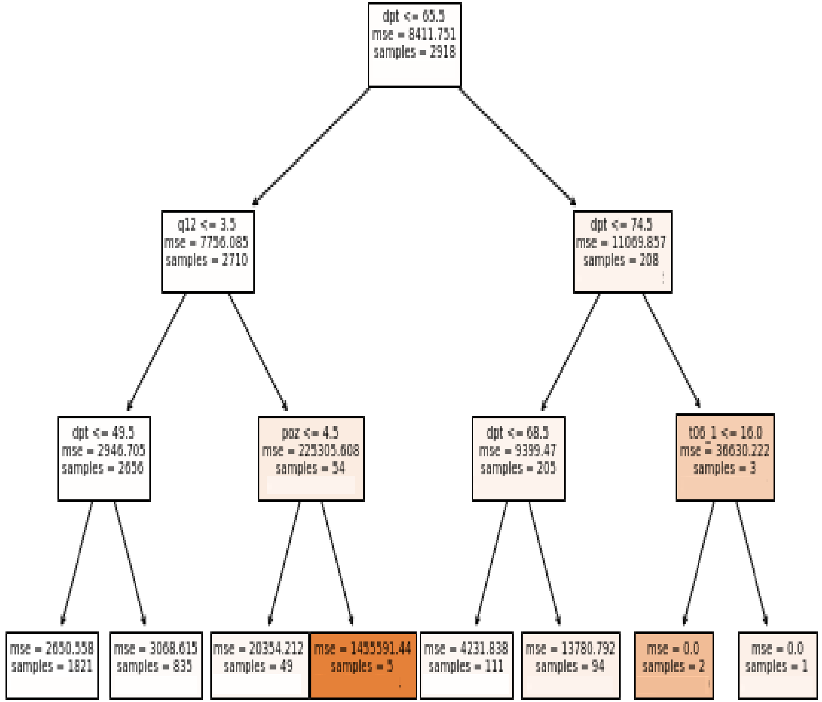


Challenges and Considerations: Bridging Physics to Forecasts

Factors included in one or more local models

- Geographic Location
- Seasonality
- Temperature
- Dew Point
- Difference between Temperature and Dew Point
- Precipitation: % chance, quantity next 12 hours
- % Chance of Thunderstorm Next 6 or 12 Hours
- Probability of Wind Gust Over 25 / 35 / 45 mph
- Wind Direction
- Visibility
- Intensification: an increase in severity of weather between the 72-hour and 48-hour forecasts

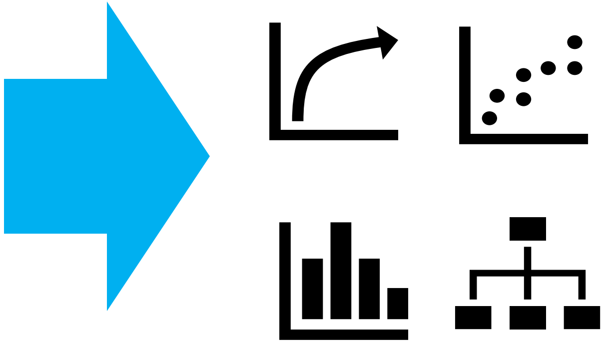
Decision Tree identifying important features



DTE Energy

SAGE

Weather Analytics: Methods and Algorithms



Methodology: Algorithms

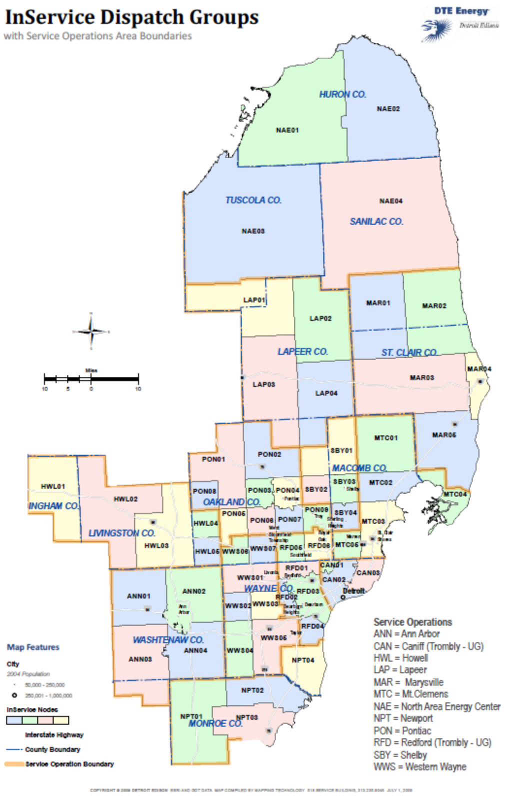
Regression-Type Methods: Predicts the Expected Number of Outages in a Day

- Multiple Linear Regression
- RandomForest
- Neural Networks - CNN and LSTM
- XGBoost

Classifier Methods: Predicts Weather Impact by Category – Normal, High, Storm, etc.

- Logistic Regression
- Decision Tree
- KNN
- SVM

Methodology: Geo-Spatial Localization and Boosting



A. Due to regional differences, each DTE Service Center gets its own model

B. Boosting: numbers for each area are added for an overall total, reducing the impact of noise

C. Localization and boosting results in more accurate predictions

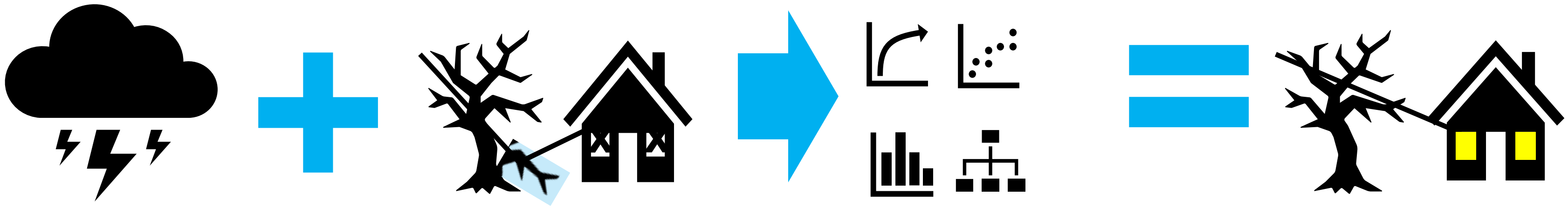
Methodology: Time Series Techniques

Sequential Model Example: Similarity Analysis

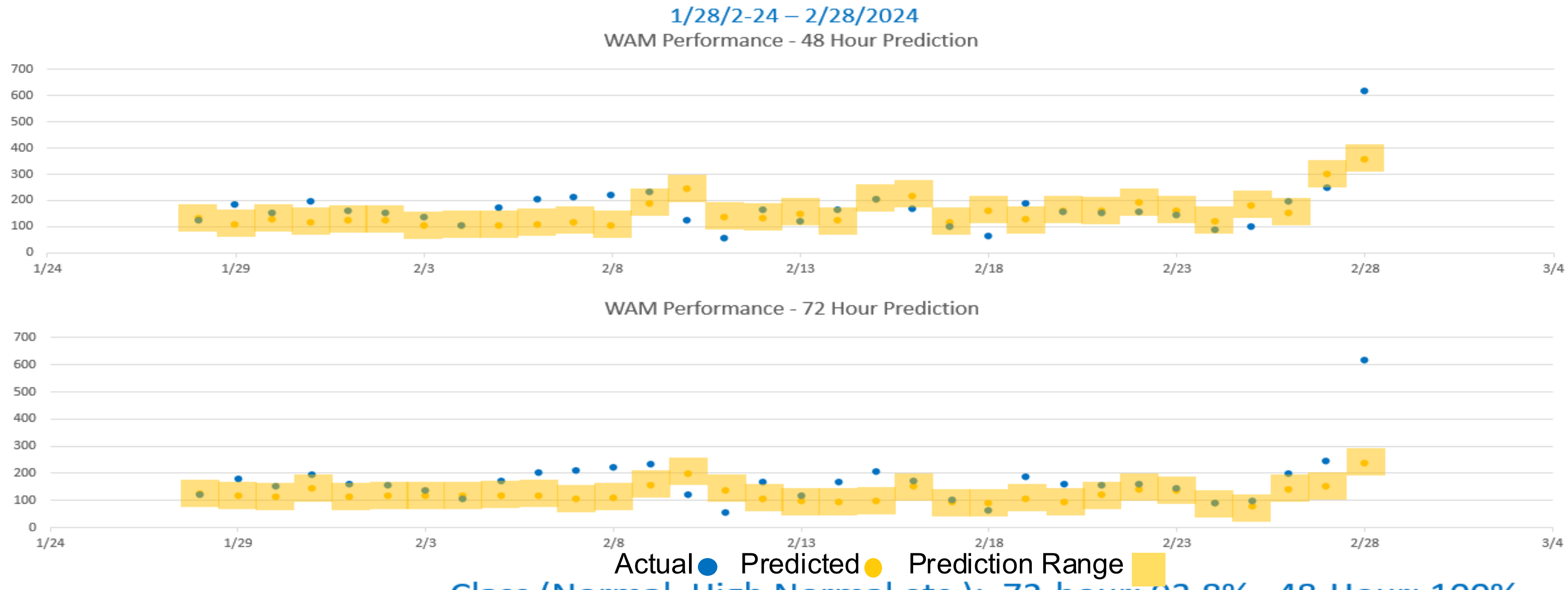
- A. Due to regional differences, each DTE Service Center gets its own model
- B. Boosting: numbers for each area are added for an overall total, reducing the impact of noise
- C. Localization and boosting results in more accurate predictions

	Cycle1	Cycle2	Cycle3	Cycle4	Cycle5	Cycle6	Cycle7	Cycle8
Cycle1	0	193.67	185.09	184.12	222.47	341.67	392.48	532.5
Cycle2	193.67	0	71.34	233.86	34.16	280.74	79.89	115.73
Cycle3	185.09	71.34	0	229.11	57.79	287.56	121.01	160.87
Cycle4	184.12	233.86	229.11	0	176.47	317.19	108.08	133.58
Cycle5	222.47	34.16	57.79	176.47	0	281.18	35.96	85.93
Cycle6	341.67	280.74	287.56	317.19	281.18	0	256.74	219.47
Cycle7	392.48	79.89	121.01	108.08	35.96	256.74	0	65.64
Cycle8	532.5	115.73	160.87	133.58	85.93	219.47	65.64	0

Weather Analytics: Results, Metrics, and Conclusions



Results: Metrics and Ensemble Model Performance



Model Accuracy

Class (Normal, High Normal etc.): 72-hour: 93.8% 48-Hour: 100%

Count (Within 50 of Actual): 72-hour: 53.1% 48-Hour: 75.0%

DTE Energy

SAGE

Results: Responsible AI Practices at DTE Energy

A **Transparency:** publicly available weather data, outage counts published via an Outage Map from DTE

B **Ethical Use:** Customer-provided outage information is used to improve service with no hidden agenda or uses

C **Bias Mitigation:** Every model tested for bias at every stage from development, data selection, and model testing

D **Commitment to Public Service:** Advanced analytics and AI applied to serve the community by strengthening and protecting electrical service

Results: Scientific Summary and Conclusions

- The DTE Energy Weather Analytics Model application predicts number of outages 48 and 72 hours in advance using weather forecast data and historical outage counts.
- Predictions are produced for outage count and impact level by date.
- Multiple model techniques are used, including regression, clustering, Decision Tree, RandomForest, CNN, and LSTM.
- An ensemble of methods provided the most accurate outage count predictions with fewest false negatives.
- A separate version of each model is developed for each local area and then added together for a system-wide total.
- CI/CD in analytics: models are constantly monitored and improved.
- Careful attention is paid to ethical best practices in model development and use.

References

1. Wadler, J. B., J. J. Cione, J. A. Zhang, E. A. Kalina, and J. Kaplan, 2022: The Effects of Environmental Wind Shear Direction on Tropical Cyclone Boundary Layer Thermodynamics and Intensity Change from Multiple Observational Datasets. Mon. Wea. Rev., 150, 115–134, https://doi.org/10.1175/MWR-D-21-0022.1.
2. Breiman L (2001). "Random Forests". Machine Learning. 45 (1): 5–32. Bibcode:2001MachL..45....5B. doi:10.1023/A:1010933404324.
3. Leutbecher, M.; Palmer, T. N. (2008-03-20). "Ensemble forecasting". Journal of Computational Physics. Predicting weather, climate and extreme events. 227 (7): 3515–3539
4. National Weather Service (2024), “NOAA Observation Systems”, https://www.weather.gov/about/observation-equipment#:~:text=While%20many%20of%20the%20important,about%20a%20subject%20or%20object
5. Pedregosa, F., Varoquaux, Ga"el, Gramfort, A., Michel, V., Thirion, B., Grisel, O., … others. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12(Oct), 2825–2830
6. Seabold, S., & Perktold, J. (2010). statsmodels: Econometric and statistical modeling with python. In 9th Python in Science Conference
7. Tervo, R., Karjalainen, J., Jung, A., (2019), "Short-term prediction of electricity outages caused by convective storms", IEEE Trans. Geosci. Remote Sens., vol. 57, no. 11, pp. 8618-8626, Nov. 2019
8. Weyn, J. A., Durran, D. R., and Caruana, R.: Can Machines Learn to Predict Weather? Using Deep Learning to Predict Gridded 500-hPa Geopotential Height From Historical Weather Data, J. Adv. Model. Earth Sy., 11, 2680–2693, https://doi.org/10.1029/2019MS001705, 2019
9. Weyn, J.; Durran, D.; Caruana, R.; Cresswell-Clay, N. Sub-seasonal forecasting with a large ensemble of deeplearning weather prediction models. J. Adv. Model. Earth Syst. 2021, 13, e2021MS002502

Questions

?

Thank You!

David J Corliss, PhD
david.corliss@dteenergy.com