



TEXAS RE

Artificial Intelligence

Faruk Dziho
BI Analytics and Data Solution Lead
Texas RE

March 10, 2026

Because this event brings together market participants who may be viewed as actual or potential competitors, we must be mindful to conduct it in a manner that is consistent with the antitrust and competition laws. Participants should not disclose non-public, proprietary, or competitively sensitive information.

Attendees should exercise independent judgment and avoid even the appearance of discussions of agreements or concerted actions that may be viewed as restraining competition. Any questions on Texas RE's Antitrust Compliance Corporate Policy may be directed to Texas RE's General Counsel.



talk with
TEXAS RE

April 8, 2026

Regional Risk Series:
Cold Weather



talk with
TEXAS RE

April 29, 2026

Regional Risk Series:
Supply Chain



talk with
TEXAS RE

May 5, 2026

Grid Forming vs Grid
Following Batteries



April 1, 2026

Spring Standards,
Security, &
Reliability
Workshop



May 13, 2026

Q2 MRC, AGR&F, and
Board Meetings



August 19, 2025

Winter
Weatherization
Workshop

Upcoming ERO Enterprise Events



Date	Event
March 12, 2026	<u>SERC 2026 Long-Term Reliability Webinar</u>
March 16, 2026	<u>Technical Talk with RF</u>
March 17, 2026	<u>Reliability & Security Workshop</u>
April 7, 2026	<u>SERC System Operator Technical Conference #1</u>

slido

Product

Solutions

Pricing

Resources

Enterprise

Log In

Sign Up

#TXRE

Joining as a participant?

Enter event code

Join an existing event

The ultimate Q&A and polling platform

Give a voice to your audience, wherever they are.

Create your own Slido event

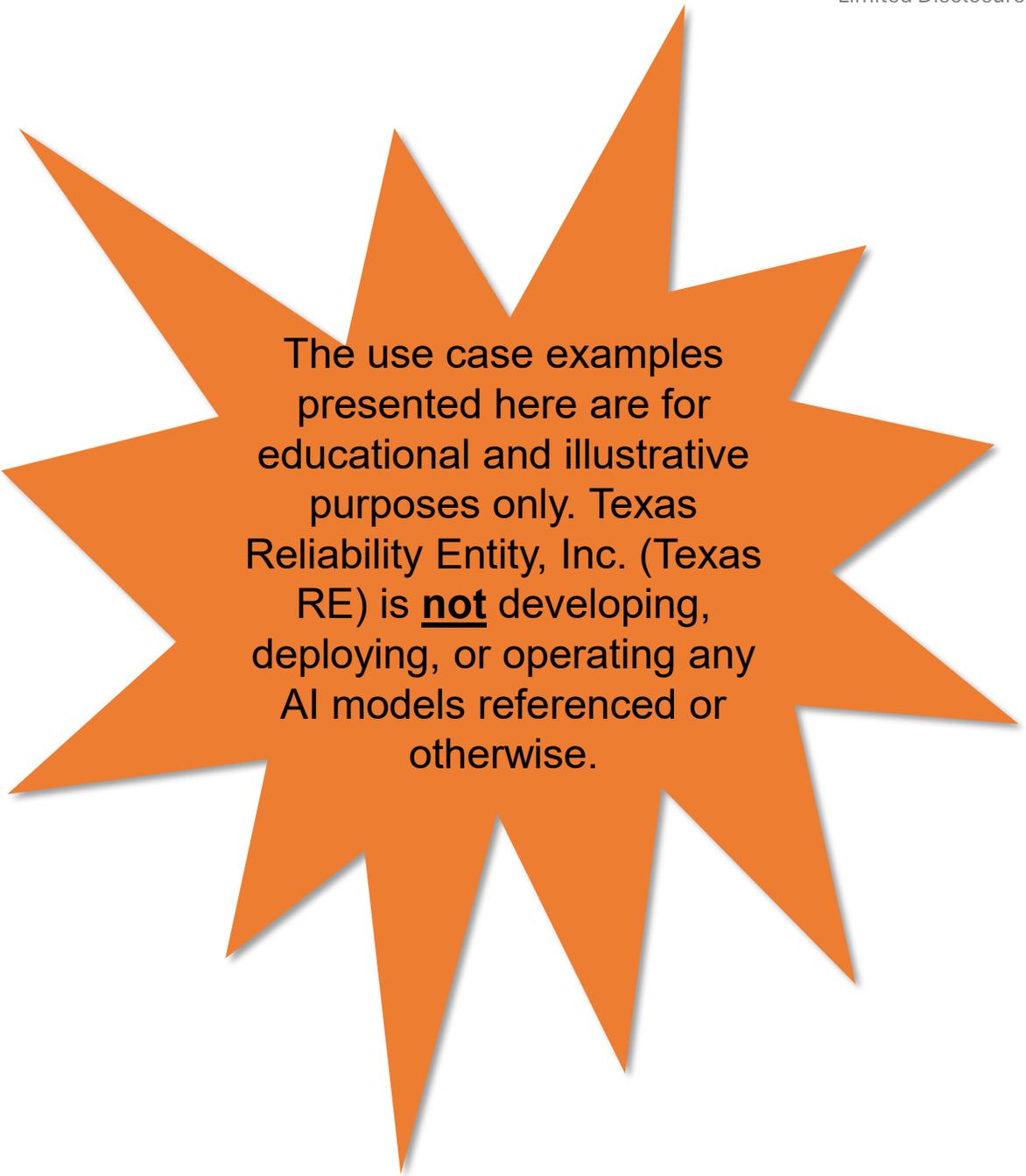
[Watch a video](#) or [Schedule a demo](#)

Artificial intelligence impact
on the industry

Demystifying AI: Overview of
the foundational AI models

Grid operations examples
using AI

Mitigating risk for AI use
cases

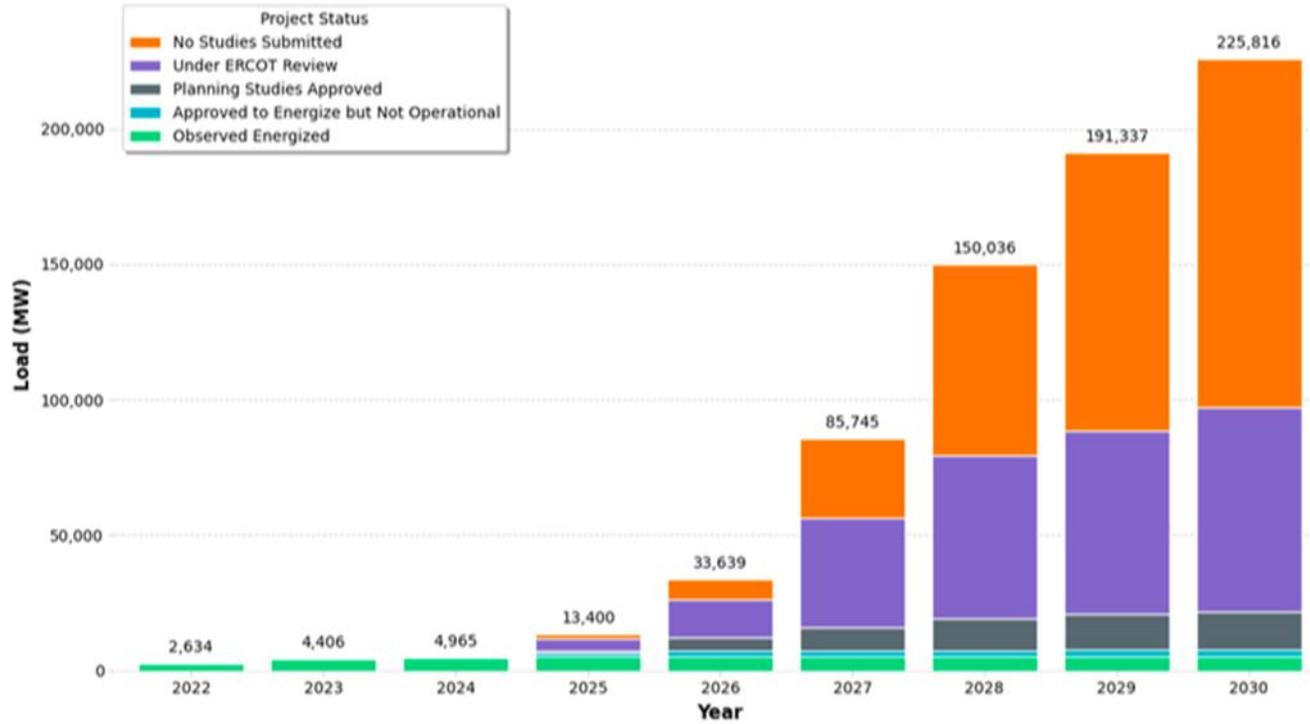


The use case examples presented here are for educational and illustrative purposes only. Texas Reliability Entity, Inc. (Texas RE) is **not** developing, deploying, or operating any AI models referenced or otherwise.

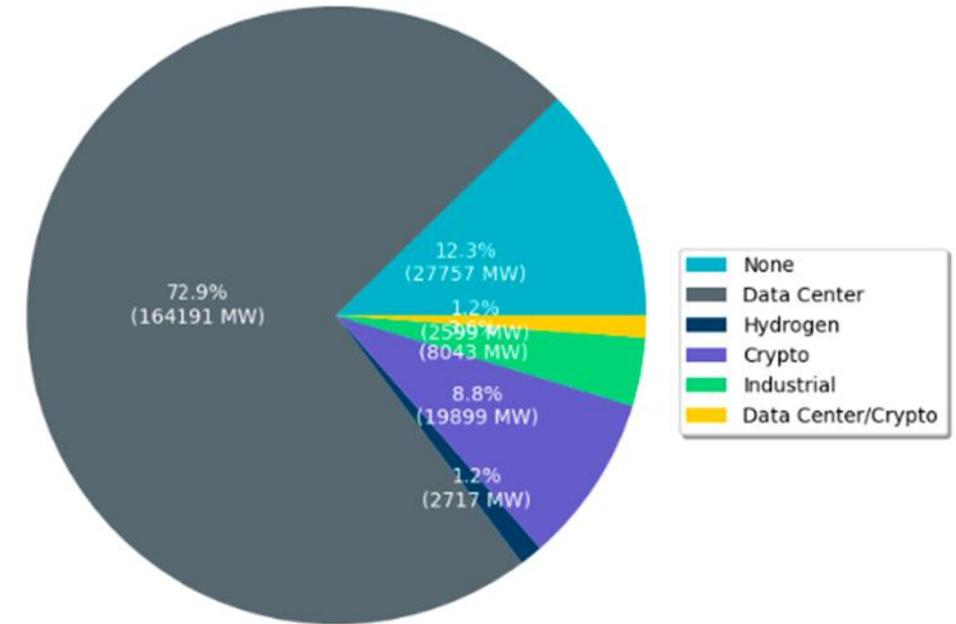
Artificial intelligence is identified as a moderate risk element in Texas RE's Reliability Performance and Regional Risk Assessment. While its potential applications show promise for the electric industry, it carries risks that demand robust mitigation strategies.

- Load growth from AI-driven activities
- Cybersecurity vulnerabilities, data issues, algorithmic errors, and the potential for misuse

Actual and Projected Large Load Growth 2022-2030



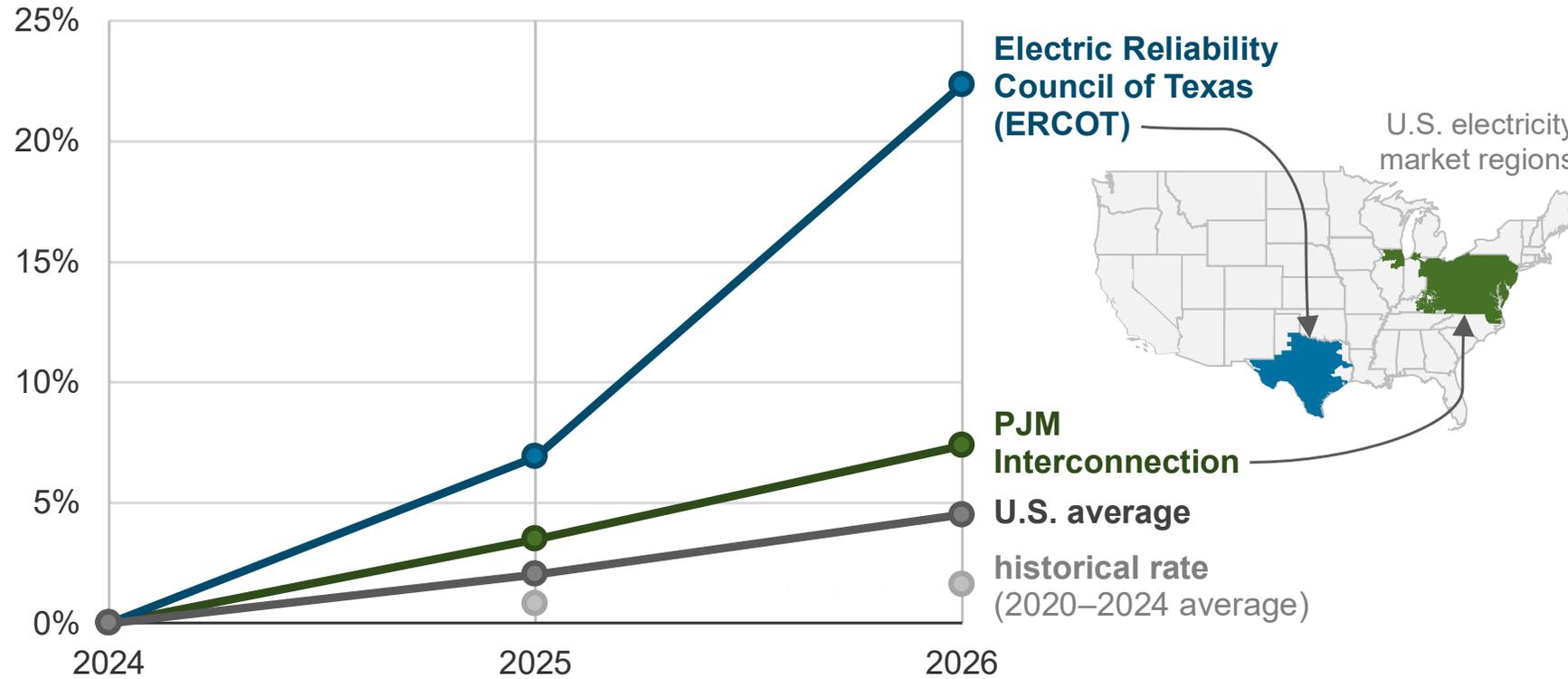
Project Status	2022	2023	2024	2025	2026	2027	2028	2029	2030
No Studies Submitted	0	0	0	1,414	7,385	29,580	70,709	102,970	128,487
Under ERCOT Review	0	0	0	4,720	13,935	40,098	59,909	67,472	75,531
Planning Studies Approved	0	0	0	637	5,118	8,866	12,217	13,394	14,297
Approved to Energize but Not Operational	0	77	131	1,327	1,899	1,899	1,899	2,199	2,199
Observed Energized	2,634	4,329	4,834	5,302	5,302	5,302	5,302	5,302	5,302
Total (MW)	2,634	4,406	4,965	13,400	33,639	85,745	150,036	191,337	225,816



Most projected growth is due to needs for computing facilities and AI

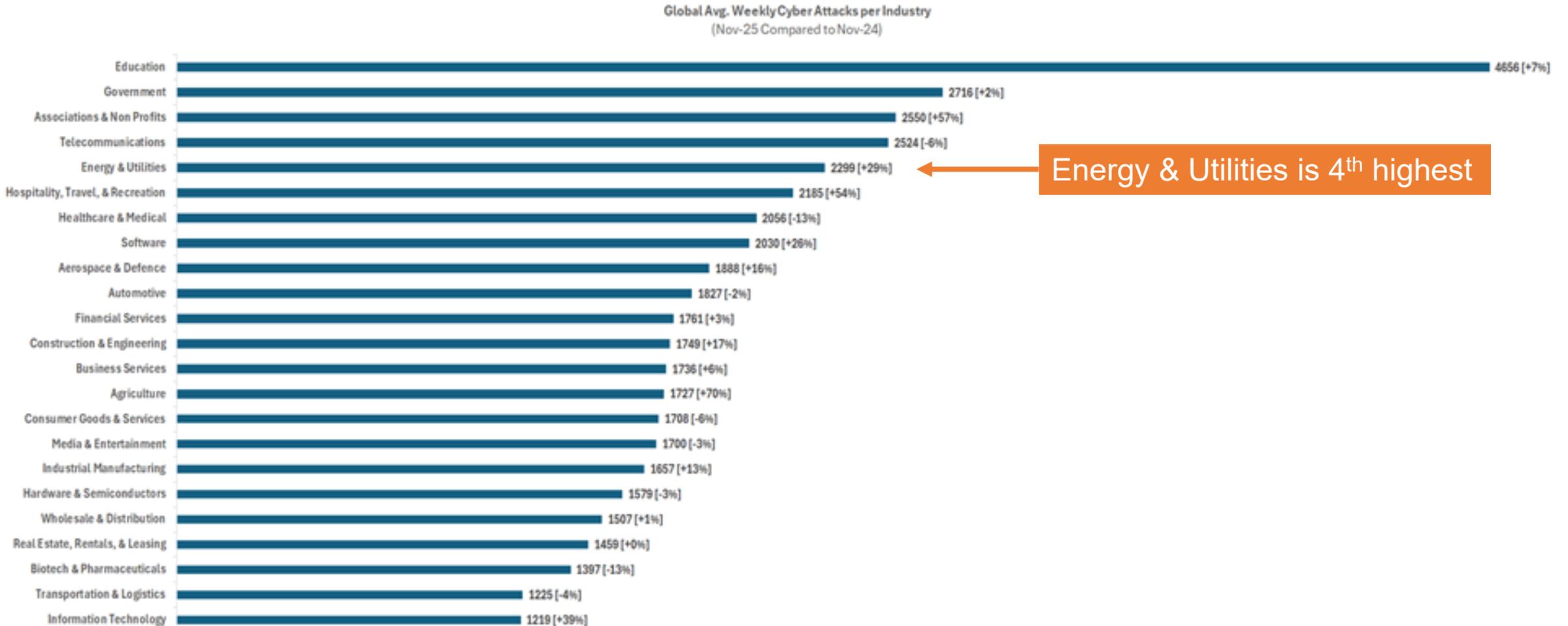
Courtesy of ERCOT

Forecast change in U.S. electricity sales to ultimate customers (2024–2026)
percentage change since 2024



EIA expects rapid electricity demand growth in Texas

Global Average Weekly Cyber Attacks per Industry



Energy & Utilities is 4th highest

Companies experienced approximately 2,000 cyber-attacks every week in 2025

Source: Check Point

Artificial Intelligence (AI): Computer systems that perform tasks normally requiring human intelligence (pattern recognition, prediction, optimization)

Today, most people associate artificial intelligence with machine learning

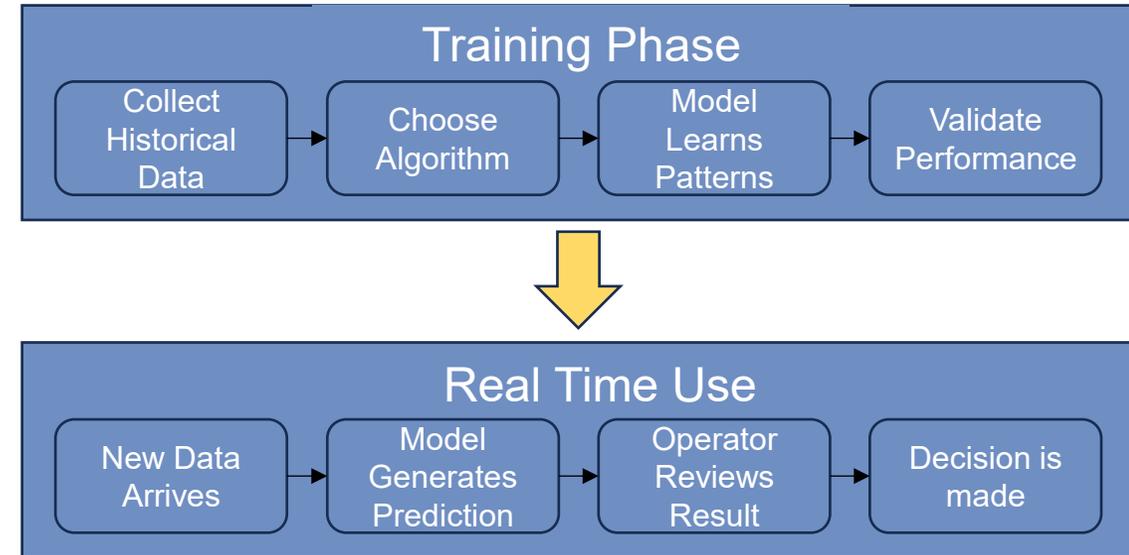
Machine Learning (ML): Systems that learn from data rather than follow hard coded instructions. Three common types of ML models are predictive, classification, and clustering

AI is ~~magic~~ applied statistics and computing at scale that supports human decisions

Inputs: Training data,
historical records

Model Learning:
Algorithms find patterns

Output: Models make
forecasts like predictions

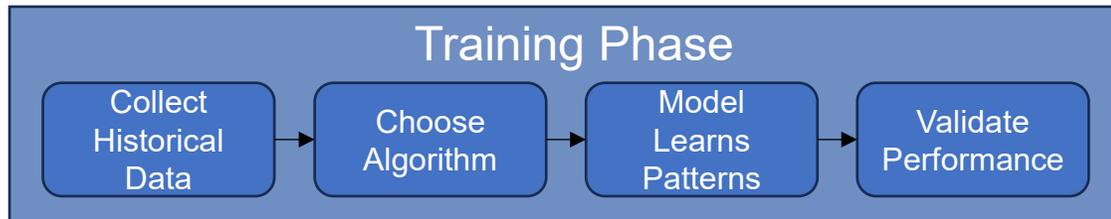


Model Type	Basic Function	Common Algorithms	Use Case Examples	Example Data Required
Predictive	Algorithms that forecast future conditions such as demand spikes or next day load	-Linear regression -Support vector regression -Random forest regression	Short-term load forecasting	Historical load + weather
Classification	Algorithms that assign categories/labels like fault detection or equipment status	-Logistic regression -Random forest classifier	Asset health monitoring	Network topology, operating conditions, metadata
Clustering	Algorithms that create groupings similar patterns such as customer usage	-K-Means -Hierarchical clustering	Outage event grouping	Outage event data, device metadata, environment data

The use case examples presented are for educational and illustrative purposes only. Texas RE is **not** developing, deploying, or operating any AI models referenced or otherwise.

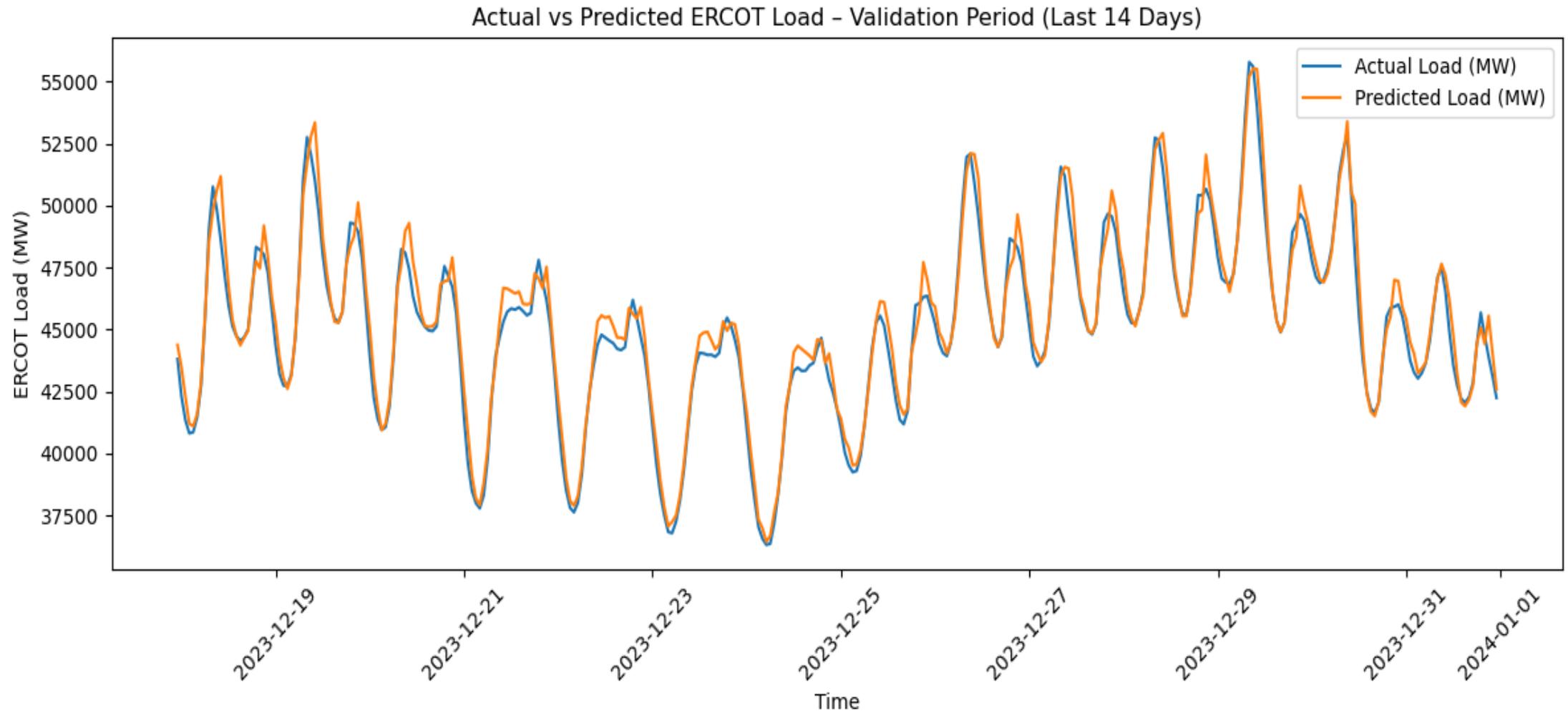
Foundational Models: Predictive Modeling Example

- ❑ Can we predict hourly ERCOT load (MW) using historical and engineered features?
- ❑ ERCOT native load dataset (2023-24)
 - Compared 4 regression models (Linear, Decision Trees, KNN, SVR)
 - Peak load 70,000-85,000 MW
 - Prediction error – 670 MW, 1-1.3% error range



Performance Metric	Meaning	Value
Mean Absolute Error	Average MW prediction error	480 MW
Root Mean Squared Error	Penalizes large forecast error	670 MW
R ² Score	Explains how much load variation the model captures	0.94

The use case examples presented are for educational and illustrative purposes only. Texas RE is **not** developing, deploying, or operating any AI models referenced or otherwise.



Foundational Models: Predictive Modeling Example (Proof of Concept)

Benefits

- Situational awareness
- Low-cost surrogate model

Limitations

- Highly dependent on data quality (ERCOT load is structured, seasonal and dependent on recent history)
- No weather features
- No holiday indicators
- No seasonal encoding

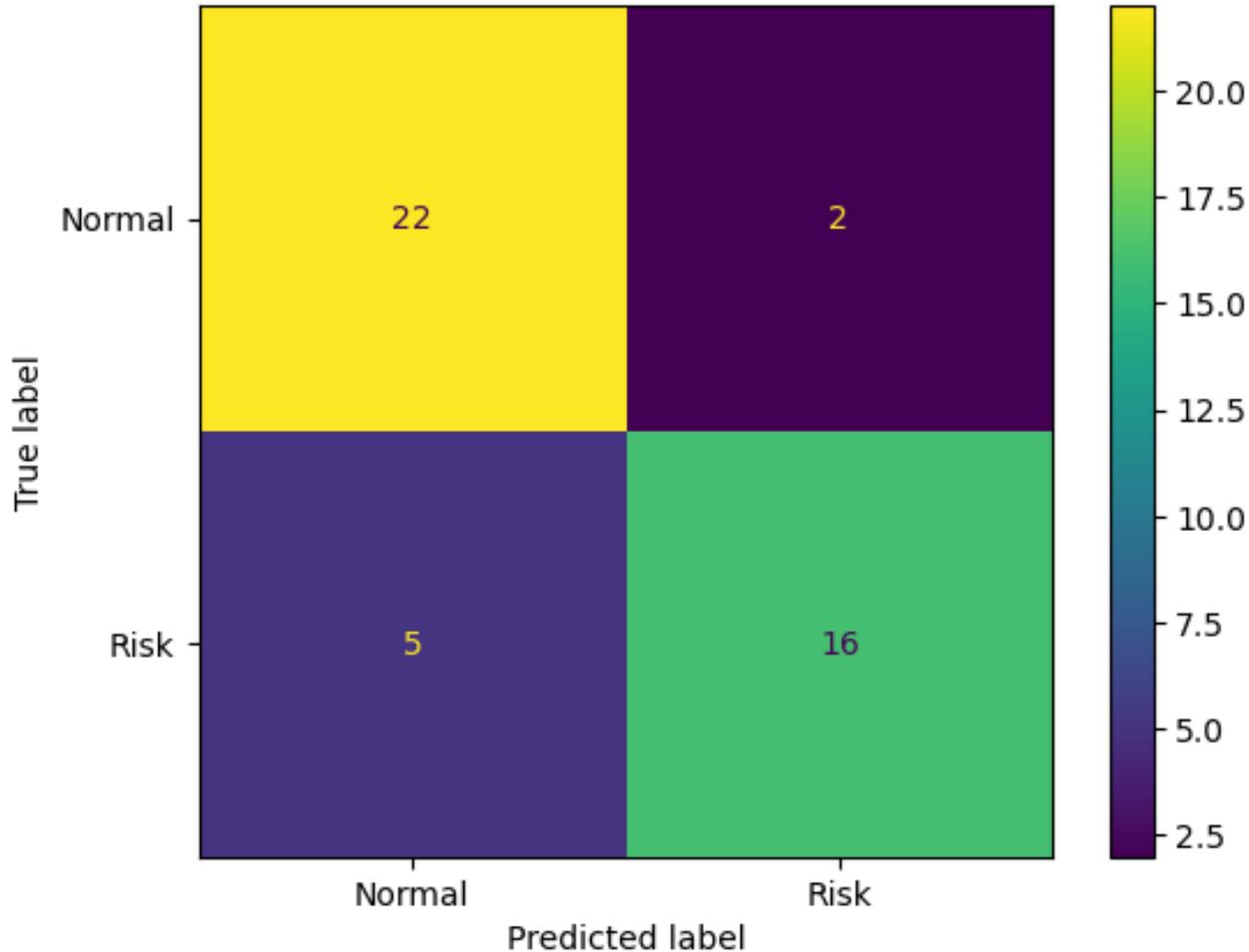
Foundational Models: Classification Modeling Example

- ❑ Based on the grid characteristics can we predict whether a bus is likely to be voltage stressed?
- ❑ 180-bus 20 kV distribution dataset from IEEE
 - Labeled buses as voltage risk and normal based on the solved power flow
 - Trained a model to predict/assign that label using network position, local demand and generation, zone/substation
 - 'Random forest' classification model learned patterns associated with voltage deviations
 - 85% accurate
 - 'Confusion matrix' is the foundation for classification model performance metrics

The use case examples presented are for educational and illustrative purposes only. Texas RE is **not** developing, deploying, or operating any AI models referenced or otherwise.

Foundational Models: Classification Modeling Example

Random Forest: Confusion Matrix (Voltage Risk Classification)



Accuracy: 0.844

Confusion Matrix:

True normal correctly predicted: 22

True normal incorrectly predicted as risk (false alarm): 2

True risk correctly predicted: 16

True risk missed: 5

Metric	Meaning	Value
Accuracy	Percentage of correct predictions	84%
Precision	False alarm rate	$16/(16+2) = 88.9\%$
Recall	Missed event rate	$16/(16+5) = 76.2\%$
F1 Score	Balance of detection vs false alarm	82%

A confusion matrix helps visualize the effectiveness of the classification model

Foundational Models: Predictive Modeling Example (Proof of Concept)

Benefits

- Support situational awareness
- Flag emerging patterns for validation

Limitations

- One static power flow
- A single snapshot
- Artificial voltage thresholds
- No contingency scenarios

AI applications augment engineering judgment

Require a lot of computing power

Large datasets

Real operational uses:

- Utilities use drones + computer vision models to inspect transmission lines (detect and assign labels – classification)
- Load forecasting (regression/time series ML)
- Dynamic line rating and asset health scoring (assign labels – classification)
- Using satellite/lidar data for vegetation management (classification/prediction/clustering)



The use case examples presented are for educational and illustrative purposes only. Texas RE is **not** developing, deploying, or operating any AI-enabled robots to assist with deep space exploration.

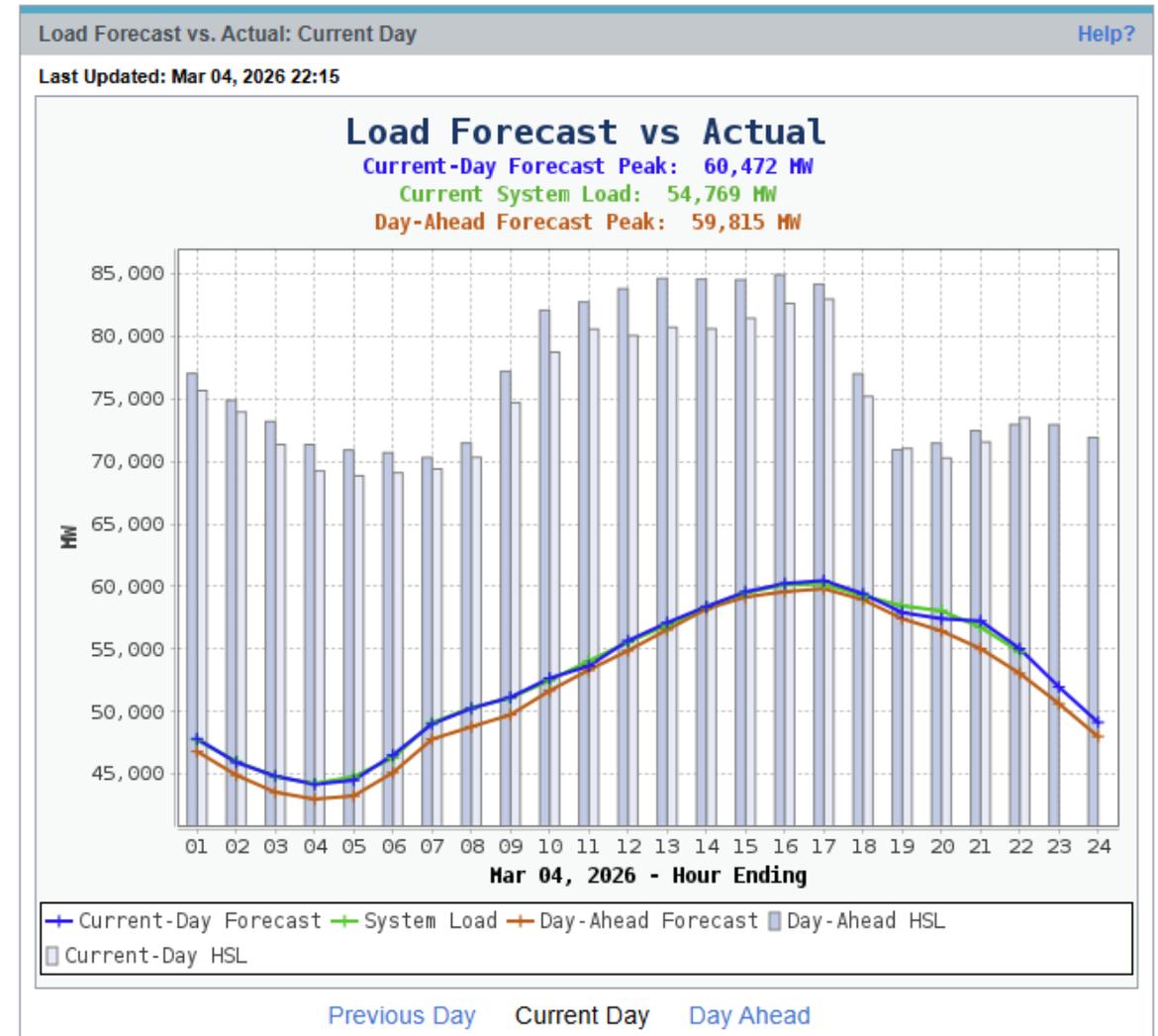
BGE: Drones + computer vision models to inspect transmission lines

- Safer
- Faster and more cost effective
- Real-time automated insights
- Detect and assign labels
- [More information](#)



ERCOT: Load Forecast vs Actual

- ERCOT provides load forecast data as compared with the actual load, as well as planned and actual on-line generation
- Predictive model based on historical weather, economic projections, and demand patterns
- [More Information](#)



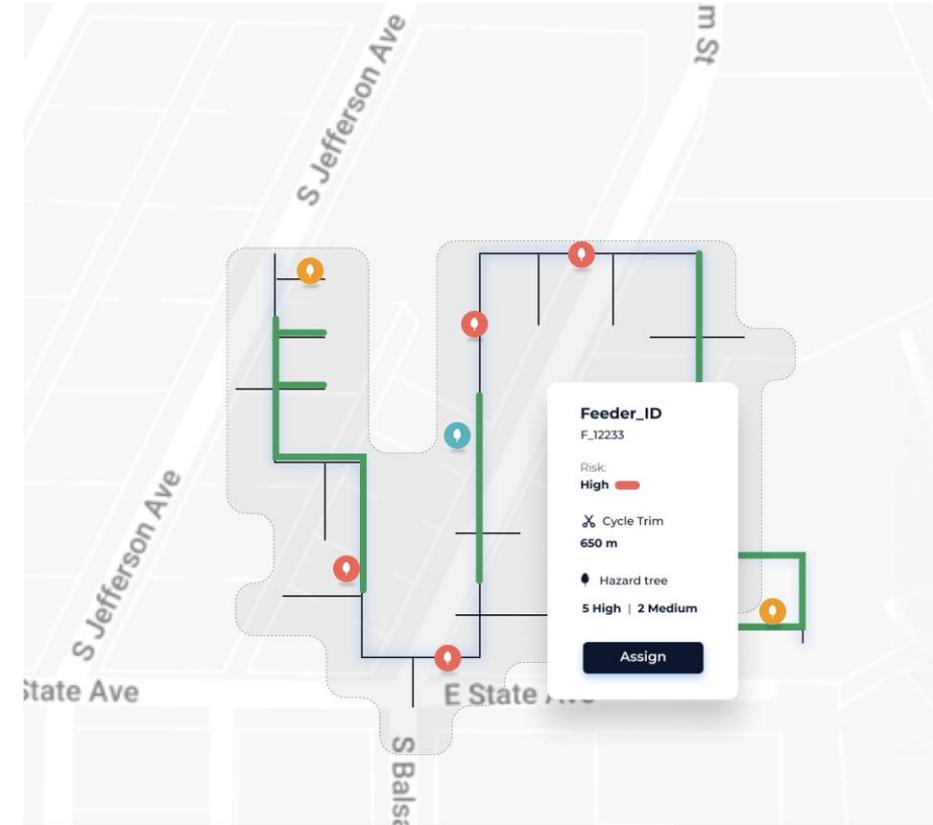
PGE: Dynamic Line Rating and Asset Health Monitoring

- Real-time insights into performance and transmission system health
- Assign labels
- [More Information](#)



AiDash: Lidar and satellite imagery for vegetation management

- National Grid is using high-resolution satellite data and AI algorithms to monitor and model vegetation growth around vital operations
- Prediction/classification/clustering
- [More Information](#)



- ❑ **AI can enhance reliability, but will create reliability risks if unmanaged**
- ❑ **AI is a tool and not a replacement for engineers or operators**
- ❑ **AI excels at pattern recognition and forecasting when there is clean data in abundance (almost never the case)**
- ❑ **Risk mitigation strategies:**
 - Robust data governance: High quality data pipelines, clear ownership and validation
 - Model transparency and oversight: Explainability and human review of AI recommendations
 - Cybersecurity integration: Secure AI workflows and role-based access
 - Regulatory and standards alignment: Fit AI adoption into existing NERC/CIP frameworks

Datasets and code used

- <https://github.com/farukdziho/aiexamples>

Questions?