# Optimizing Preventive Maintenance Frequencies

## The Case of High Voltage Breaker Diagnostic Testing

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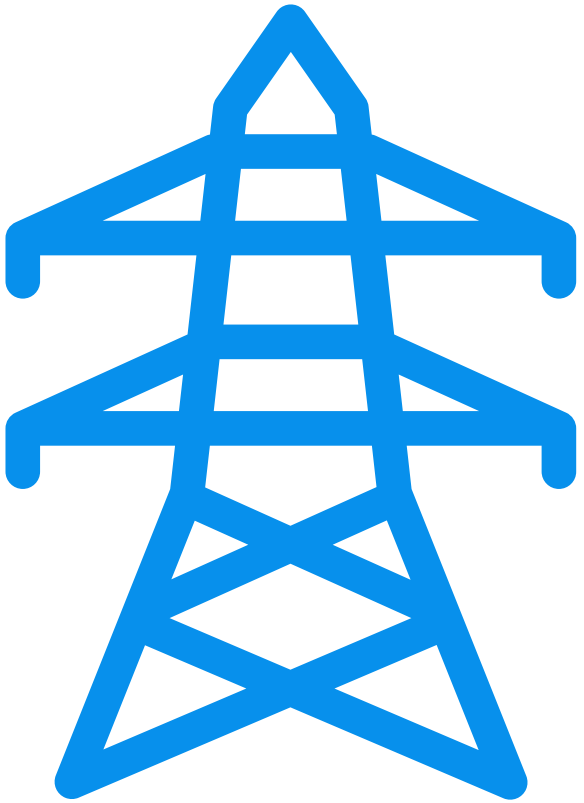
# Presentation Outline

- Con Edison's HV breaker program
- Preventive maintenance (PM) strategy
- HV breaker DT frequency analysis
  - Data collection and exploration
  - Machine learning (ML) model fitting
  - Inference & optimization
- Lessons learned & key takeaways



# Project Overview

- A few years ago, Con Ed decreased the frequency of diagnostic tests (DTs) on high-voltage (HV) breakers from every 5 years to every 7 years
  - This was based on subject matter expertise and operating experience
  - Was this a good move? Could they go even longer?
- What can we learn from 12 years of maintenance data?
  - Assess/predict how DT frequency impacts CM (Corrective Maintenance) needs
  - Recommend how frequently to do DTs to minimize total maintenance costs (DT + CM)

Image credit: https://electrical-engineering-portal.com/wp-content/uploads/2018/05/high-voltage-circuit-breakers-fundamentals.jpg

# PM FREQUENCY OPTIMIZATION

- Preventive Maintenance (PM) is a core part of any equipment maintenance program
  - Ensures equipment is running properly
  - Enables early issue detection
  - Complies with standards and regulations
- Need to find the PM “sweet spot”
  - Too much PM can be a waste of resources and create additional maintenance issues
  - Too little PM can lead to high corrective maintenance (CM) costs and reliability issues

*Image generated with AI using DALL-E 3*

# OPTIMIZING HV BREAKER DT FREQUENCIES

## Gather Data

- Collect asset & maintenance history data
- Find CM hours that occur between PMs

## Explore Data

- Check frequencies & distributions
- Select features for predicting CM hours

## Fit ML Models

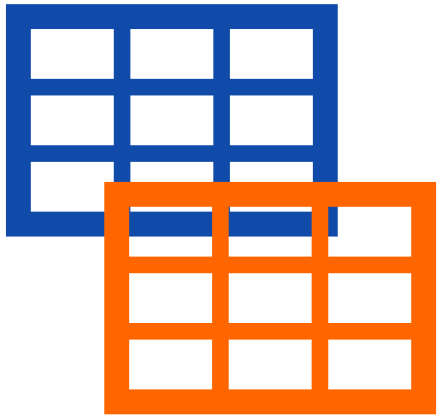
- Regression to predict CM labor hours
- Train & evaluate multiple algorithms

## Run & Optimize

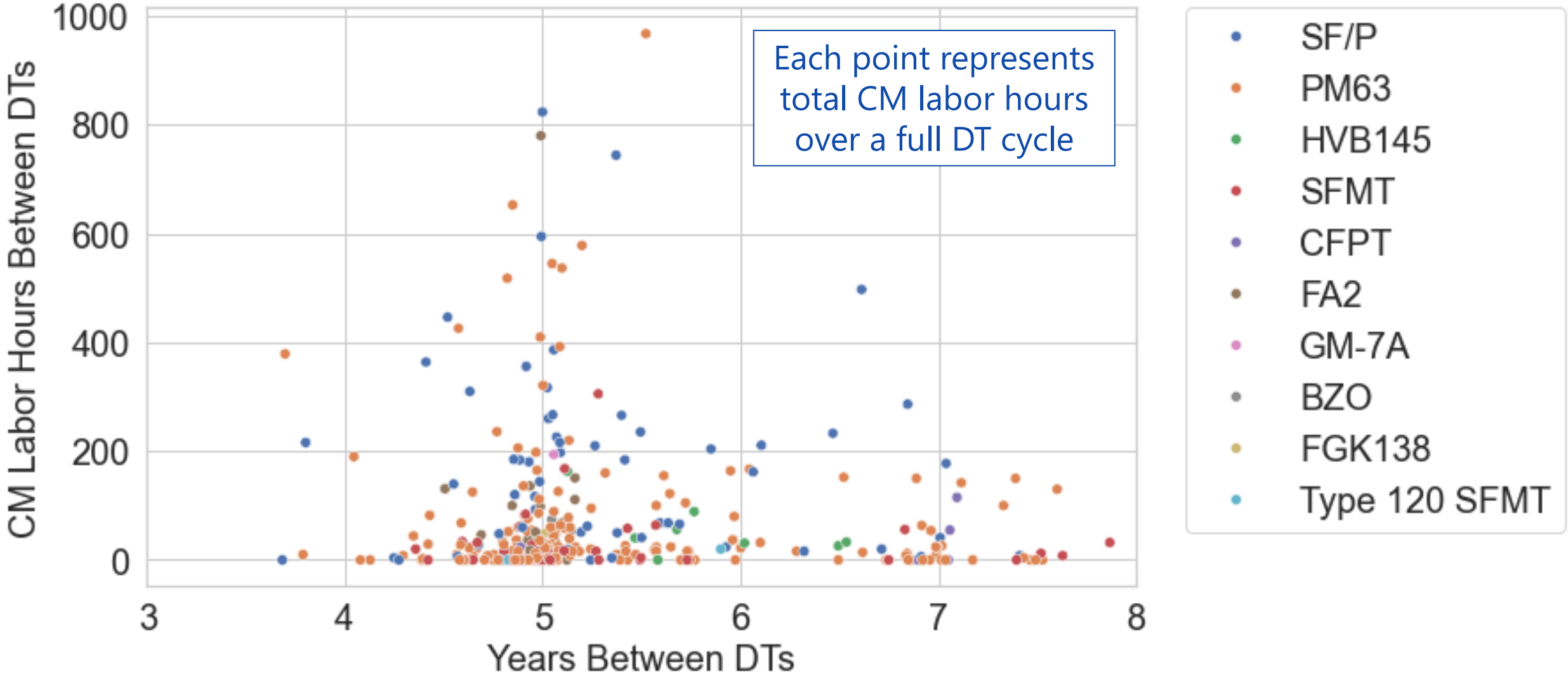
- Run model at different PM intervals
- Recommend PM frequency to minimize labor hours

# DATA OVERVIEW

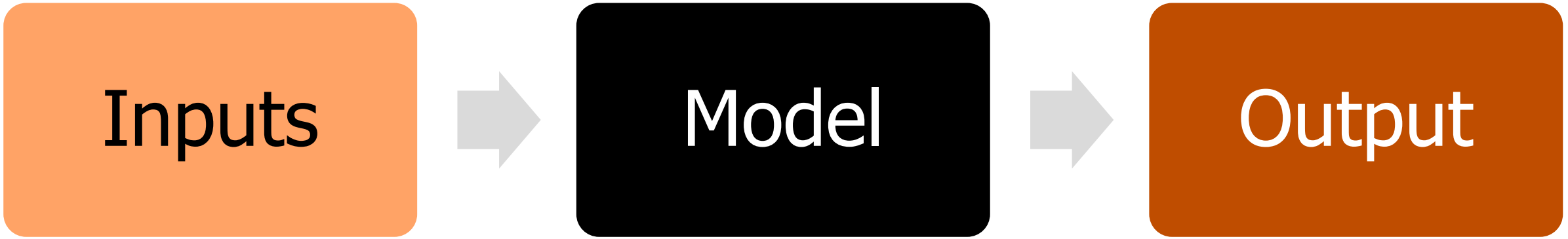
- Diagnostic test (DT) records
  - 1,590 DTs on 495 breakers over 13 years
  - Only ~5 failed DTs per year
- Corrective maintenance (CM) records
  - 11,486 CM activities
  - Data quality concerns re. which DTs/PMs/CMs were charged
- Merged dataset
  - For each DT, calculate CM labor hours on that asset from end of DT through end of next DT
  - Avg ~100 CM labor hours per asset between DTs
  - 601 DTs with a complete DT interval that follows



# DATA EXPLORATION



# MACHINE LEARNING (ML) ARCHITECTURE



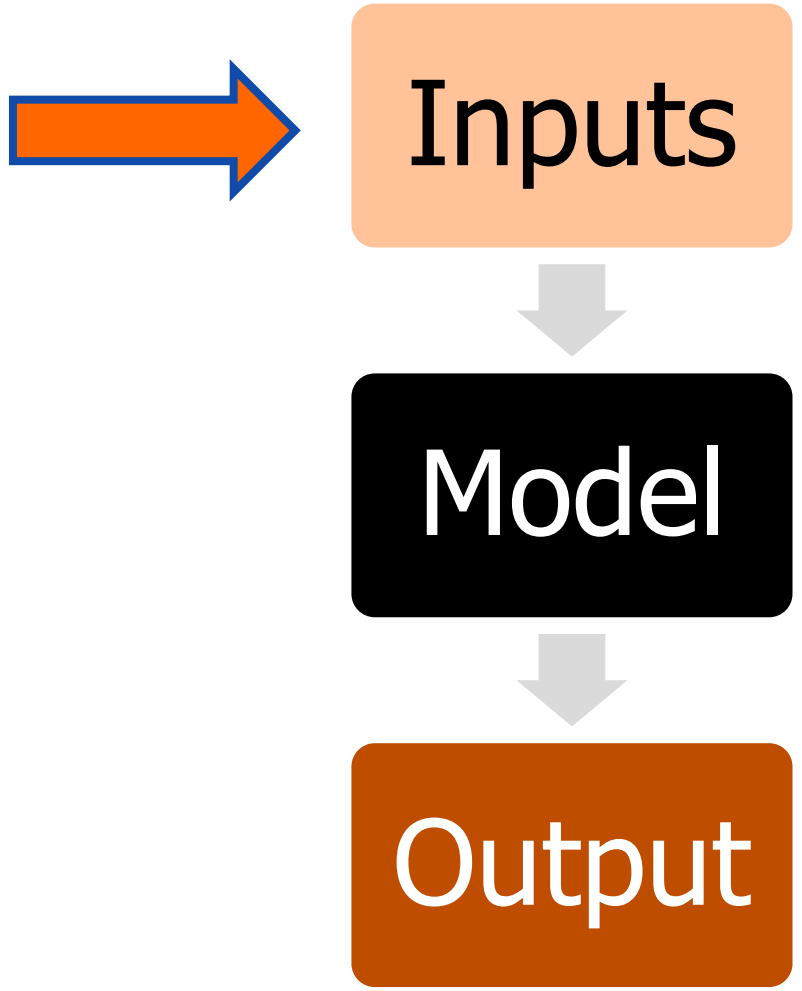

Breaker specifications
Breaker location
DT labor hours
DT frequency

Pre-trained machine learning (ML) model

CM labor hours between DTs

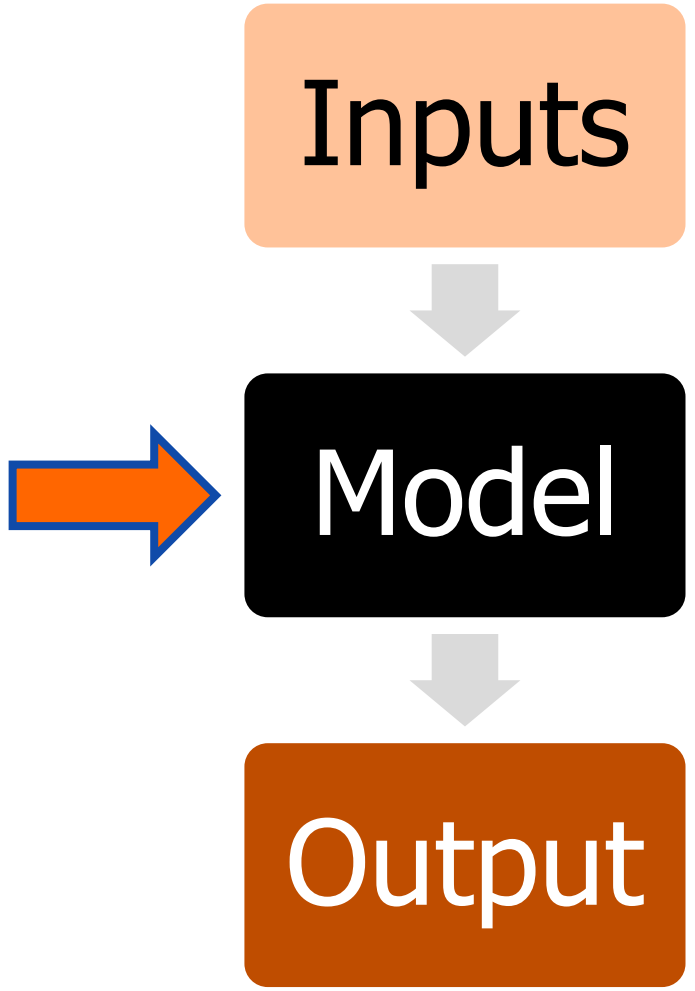
# INPUTS (FEATURES) SELECTED

- Categorical
  - Manufacturer & model
  - Location (region & station)
  - Voltage (69, 138, or 345 kV)
  - Insulating medium (SF6, air, or oil)
- Numerical
  - DT frequency
  - Actual labor hours of DT
  - Asset age



# MACHINE LEARNING APPROACH

1. **Exploration:** Train and evaluate model alternatives
   - Test multiple algorithms & settings
   - Use train/test sets with cross-validation
2. **Training:** Select & train final model
3. **Inference:** Run each breaker through model across a range of DT intervals to observe predicted trends



# GRADIENT BOOST ML MODEL

- Quality of fit
  - $R^2 = 0.975$
  - RMSE = 30 (CM labor hours)
  - Compare to dataset average 55, range 0-1000
- Useful for exploring behavior/trends, not for accurately predicting labor hours

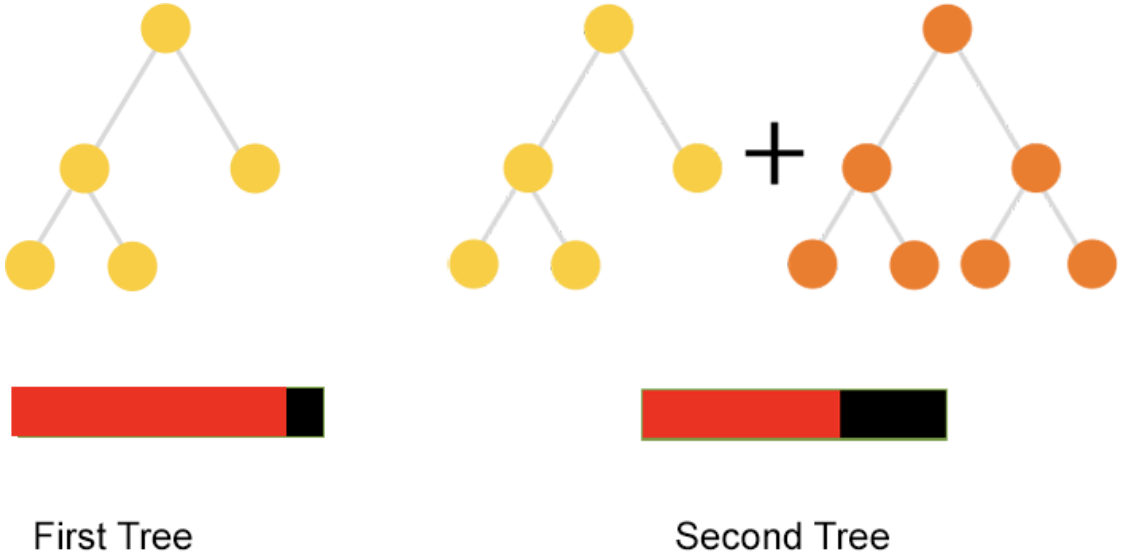
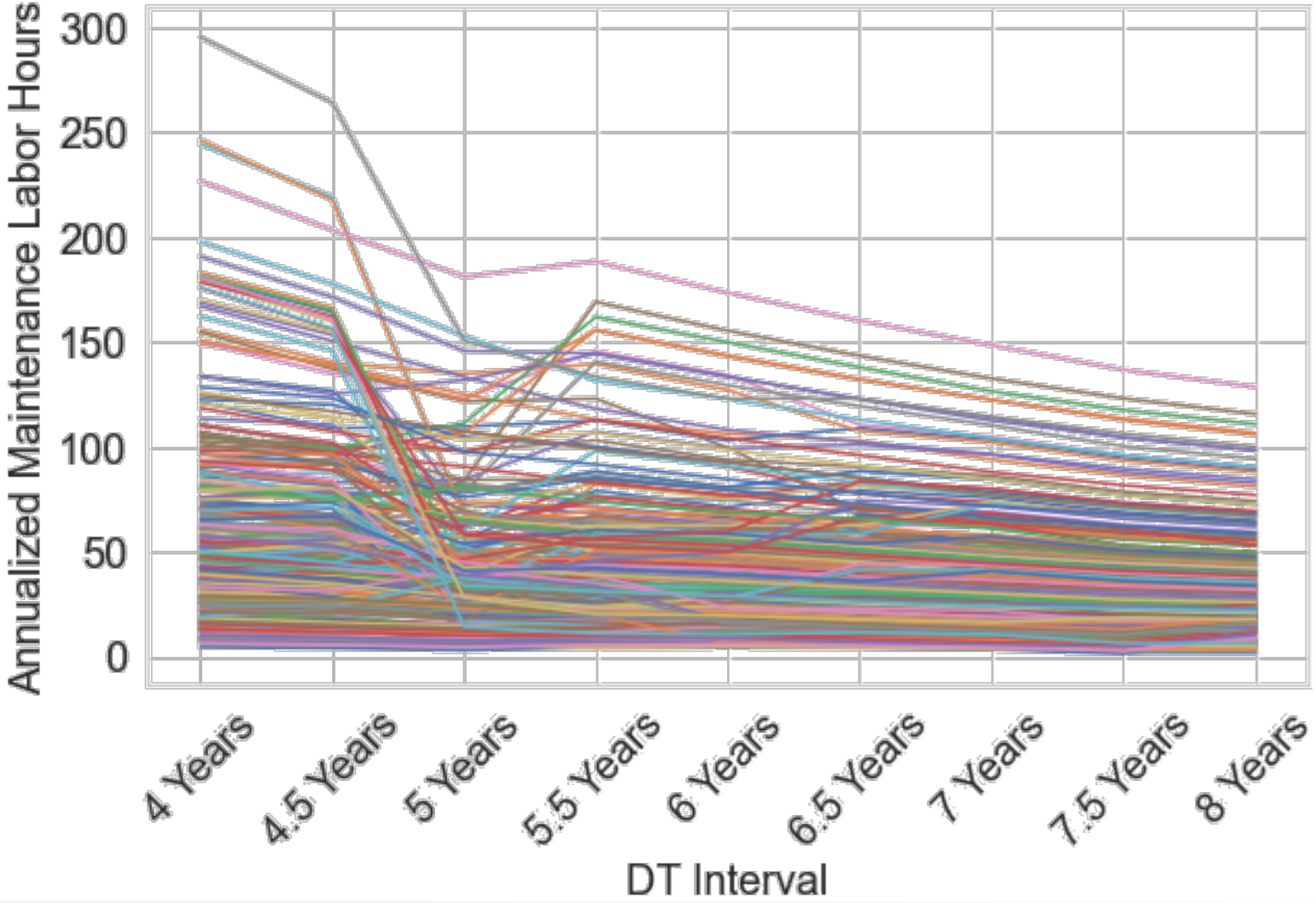


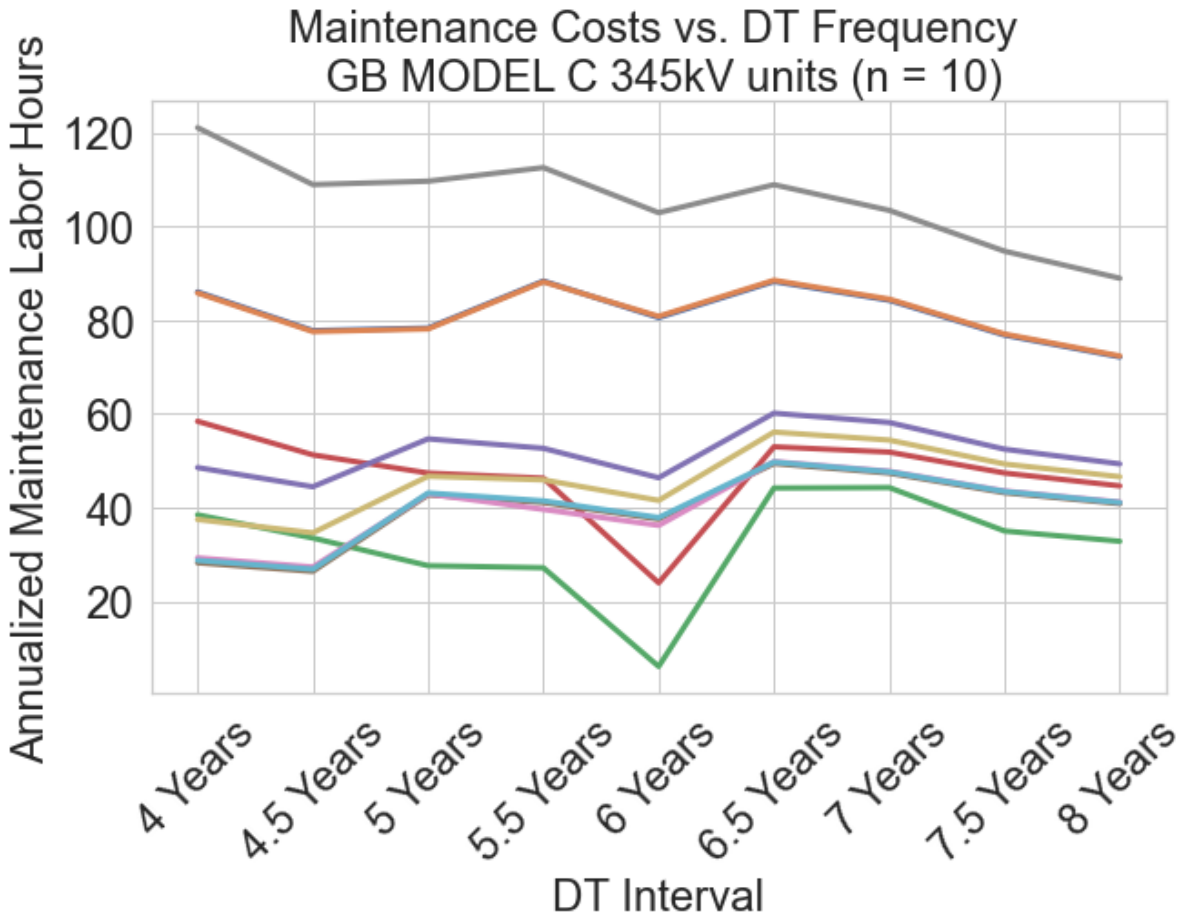

Image credit: https://catboost.ai/news/catboost-enables-fast-gradient-boosting-on-decision-trees-using-gpus

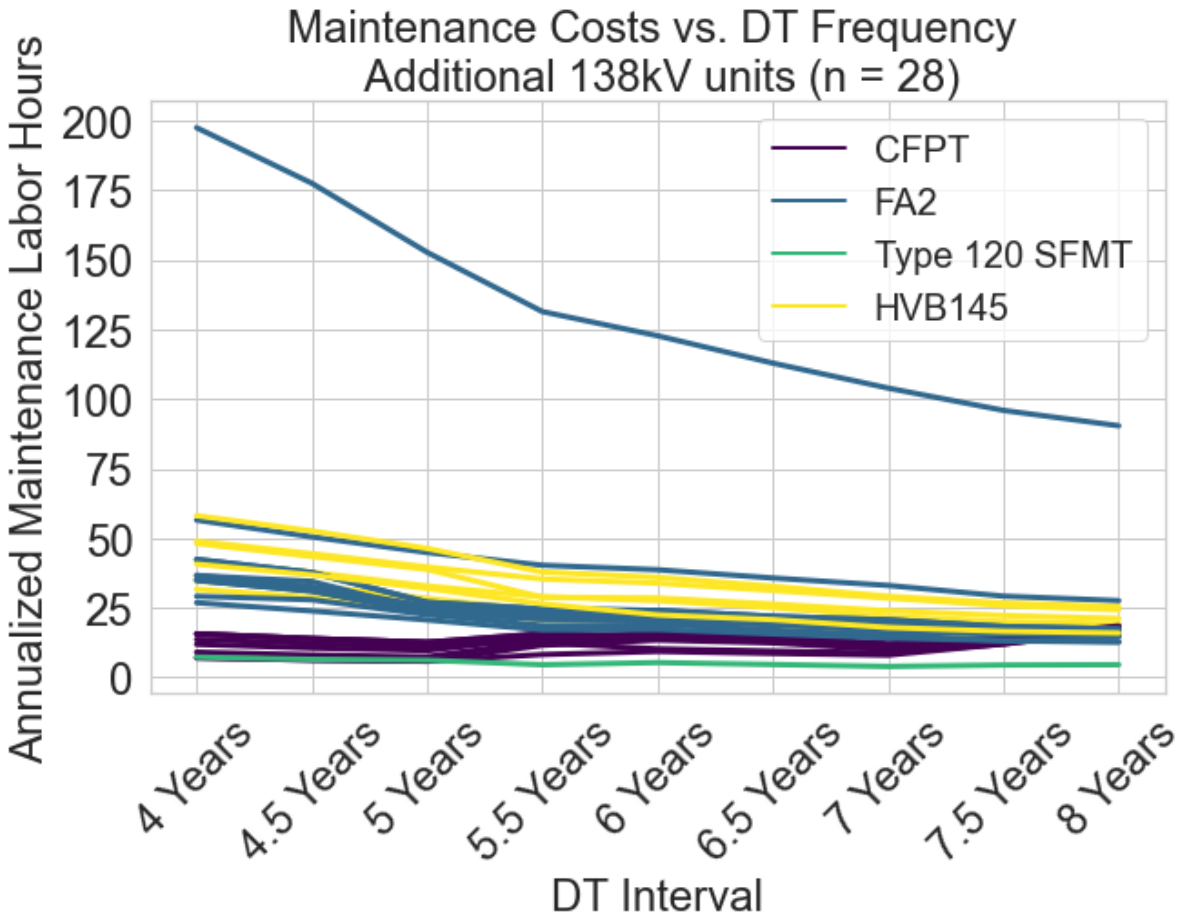
# INFERENCE RESULTS BY ASSET

- Ran each breaker through ML model
- What are expected annual maintenance hours at different DT intervals?



# INFERENCE RESULTS BY MODEL



# FITTING TRENDLINES

- Many plots have unclear/non-obvious trends
- To quantify the behavior, we fit linear trendlines
- Slope tells us direction of trend, *p*-value tells us confidence in trend

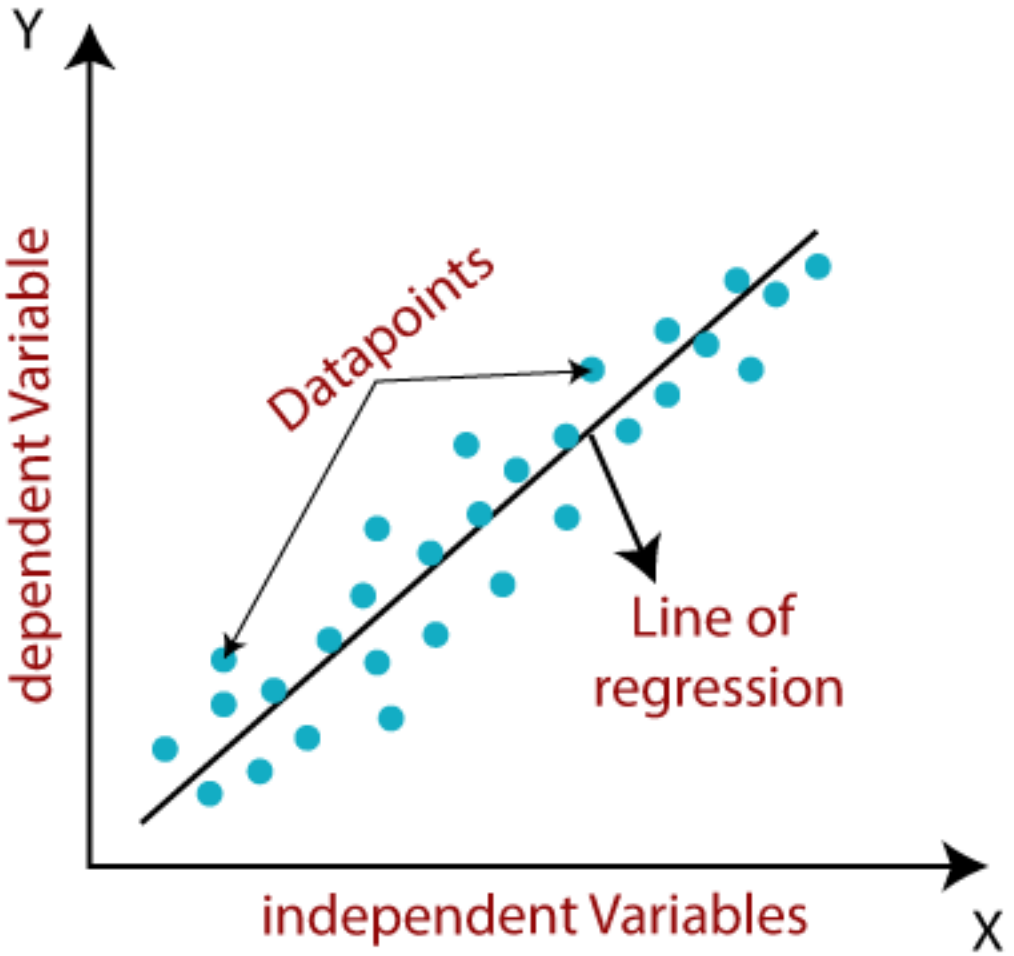
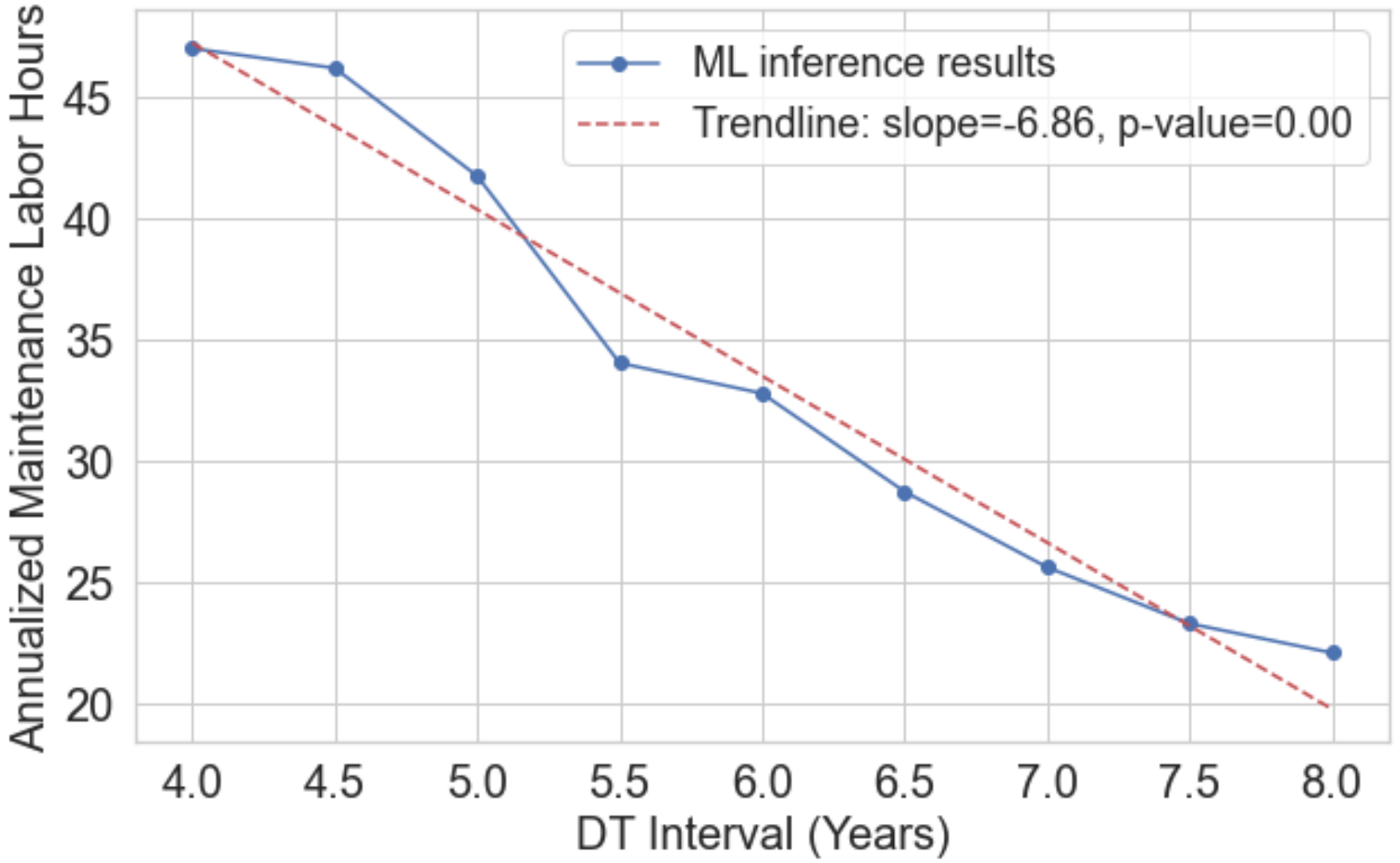
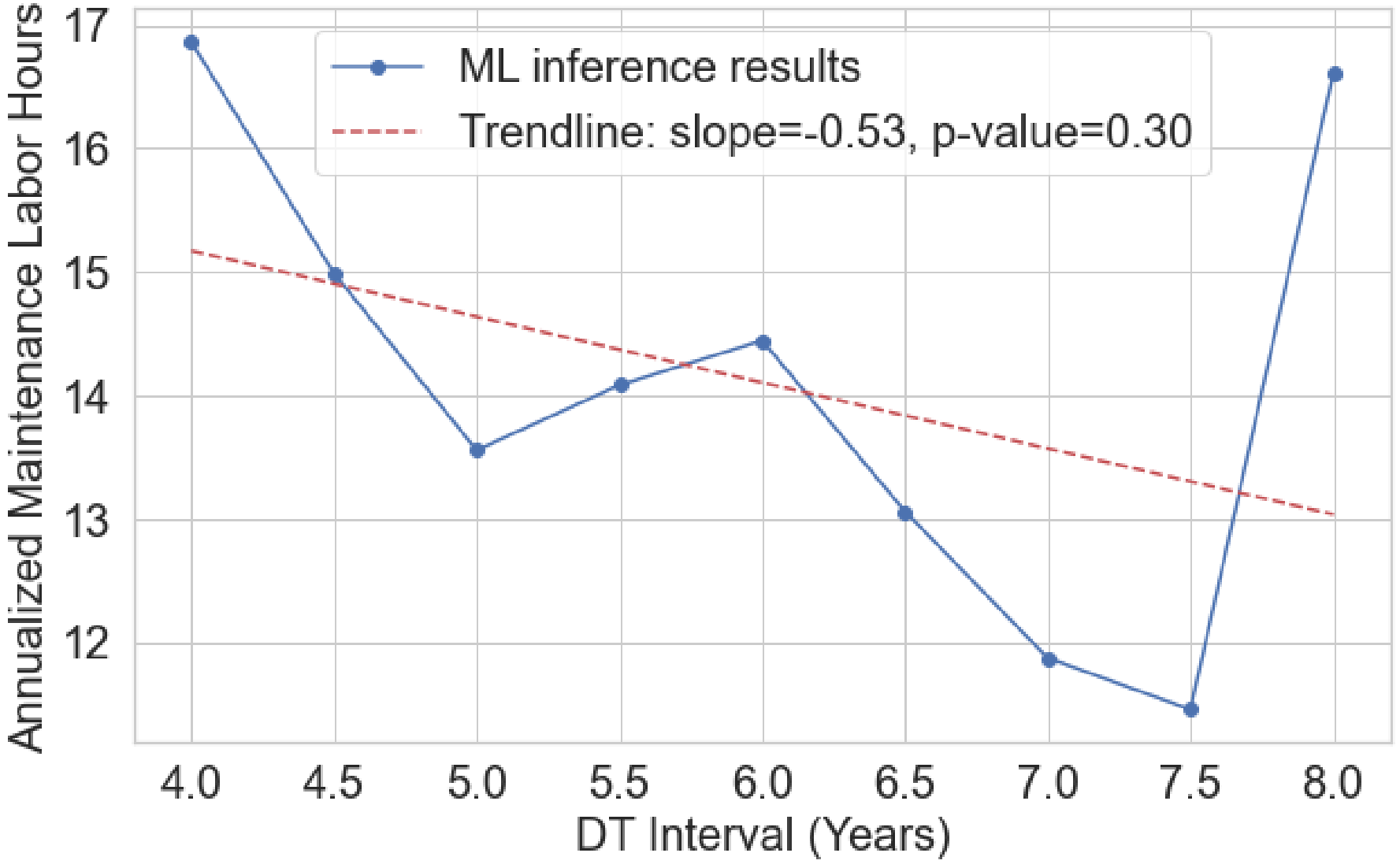



Image credit: https://pub.towardsai.net/linear-regression-explained-f5cc85ae2c5c

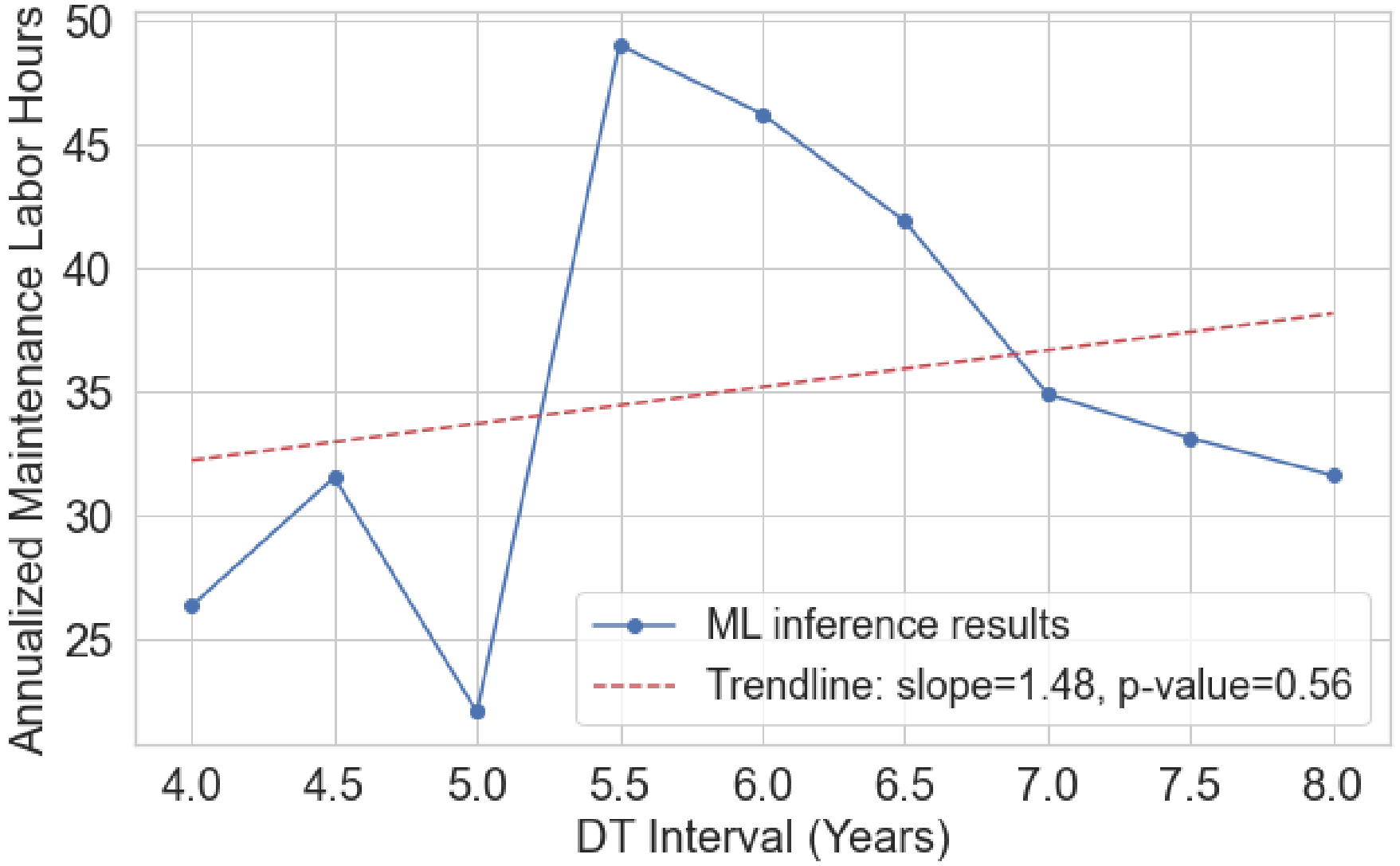
# CLEAR DOWNWARD TREND (62% OF BREAKERS)



# UNCLEAR DOWNWARD TREND (20% OF BREAKERS)

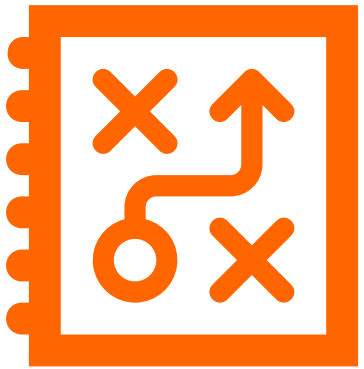


# UPWARD TREND (18% OF BREAKERS)



# RECOMMENDATIONS

- Overall: For most HV breakers, total maintenance costs should go down with longer DT intervals



- Three alternative strategies proposed:
  - Strategy A: Adjust DT intervals by specific breaker
  - Strategy B: Adjust DT intervals by model
  - Strategy C: Adjust by model, then fine-tune by asset risk

# CHALLENGES AND LESSONS LEARNED

- Data
  - Despite 13 years of data, only 601 samples
  - Changes in data collection over time influence data quality/consistency
  - No data available with DTs more than 8 years apart
  - Intimate knowledge of dataset is needed for meaningful ML

- Process
  - Close collaboration between SMEs and ML/AI team essential
  - Scope out data & model architecture prior to project commitment

# THANK YOU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