February 2024

Southern California Edison Co. Risk-Informed PSPS Model

Overview

This document is a comprehensive guide to the work done on the Public Safety Power Shutoff (PSPS) Risk-Informed Threshold (RIT) model to support Southern California Edison's ongoing public safety efforts.

Background

Southern California Edison Co. (SCE) is committed to protecting customers and communities in its service territory from wildfires during severe weather conditions. An example of these conditions is extreme wind speed, which has the potential to cause ignitions when debris or vegetation contact energized lines. To that end, SCE seeks to harness the full power of its data and advanced analytics capabilities to build a wind speed threshold model to accurately predict risk during high-speed wind events and inform PSPS decisions. Advancing an existing PSPS methodology, SCE seeks to develop a more predictive and risk-driven model that can derive wind speed thresholds with a high degree of granularity, so PSPS decisions can be accurately informed at the individual segments and circuits.

What follows is a technical whitepaper covering the creation of a model for the purpose of deriving risk informed PSPS thresholds. The long-term goal of this model is to improve public safety while minimizing interruptions to the customer.

Business Question Addressed

Given real-time information about a specific power distribution circuit segment, can we predict whether equipment in that segment will fail, potentially causing a catastrophic fire? Can we use those predictions to derive activation and de-energization thresholds that will reduce the likelihood of a fire while at the same time reducing service interruptions for the customer?

SCOPE

DELIVERABLES

✅ This report includes:

- Models that predict the real-time likelihood of failure of over-head equipment on distribution segments
- Probability of failure of distribution segments as a function of wind speed, and derived PSPS wind speed thresholds for each segment
- A back-casting plan that seeks to understand how the new risk-informed methodology would perform against the current methodology in a de-activation scenario
- Recommendations on next steps to improve the models

❌ This report does not include:

- Models that predict the likelihood of failure of underground equipment or equipment on transmission circuits
- Results from a back-casting test that seeks to understand how the new risk-informed methodology would perform against the current methodology in an activation scenario

GEOGRAPHY

The territory included in this methodology covers areas within SCE's service territory which have been categorized as high fire risk areas (HFRAs).

APPLIED USES

A model capable of predicting failures in real-time could be used as both a scenario planning tool as well as a mitigation planning tool. The segment-level model can be used, in conjunction with FPI as a risk proxy, to derive wind speed and wind gust thresholds for each segment (during the pre-planning phase prior to wildfire season, or during the event planning phase of any critical weather event). In addition, the segment-level model, as well as asset level models, can be used as predictive maintenance models to priority equipment, segments, and circuits for inspection and mitigation.

Data Sources

The following data sources used to train the failure-prediction models and to perform model evaluation were provided by SCE. These data sources are not publicly available and should be considered confidential.

Weather Data

Source	Downloadable from SCE SharePoint. Contact: [redacted]
Data file(s)	• Fire potential index data (FPI.csv). • Ignition component data (IC_points.csv). • Wind speed and wind gust ML data (Wind_and_Gust_ML.csv). • Wind direction data (Direction_points.csv). • Precipitation data (Precip_points.csv). • Temperature data (T_points.csv). • Dew point depression data (DD_points.csv). • Relative humidity data (RH_points.csv). • Solar radiation data (ShortWaveFlux.csv). • Grid cell centroid data (grid_mask.csv).
Last Updated	Data Pull: September, 2023
Frequency of Update	Manual pull
Historic Availability	From the beginning of 2020 to the end of August 2023, except for Wind speed and wind gust ML data, which is only available to the end of 2022.

These data sources contain weather data for HFRAs only. Weather data is provided for each grid cell (2km by 2km area) every hour, for 4048 grid cells that cover the HFRAs.

All weather datasets are provided in “wide table” format, i.e., each row represents a specific date and time, and there are multiples columns that represent 4048 grid cells. We pivot and join all weather datasets to create a single dataset in “long table” format, where each row represents a specific grid cell at a specific date and time; and each column represents one weather data such as temperature or humidity. This weather dataset will be joined to asset data, such as pole and conductor, to learn how weather conditions impact assets.

Since incidents (e.g., equipment failures) are reported by dates and locations, we cannot relate incidents to the hourly weather conditions. Therefore, we aggregate weather conditions by day, keeping the daily minimum, average, maximum, and standard deviation values for each weather condition.

We relate weather conditions to poles and functional locations (FLOC) based on position (latitude, longitude). A pole or a FLOC is assigned to its nearest grid cell based on its distance to the grid cell centroid. Weather conditions of a pole or a FLOC are the same as weather conditions reported for its nearest grid cell. Identifying nearest grid cells is done as a spatial join using the *geopandas* python library.

ASSET DATA

Source	Downloadable from SCE SharePoint. Contact: [redacted] for capacitor, transformer and switch data. [redacted] for pole data. [redacted] for SPIDA pole and conductor data.

Data file(s)	• Capacitor data (WORK_QUERY_FOR_STG_EQMASTER_Capacitors.csv).
	• Transformer data (xfmr_oh20230713.csv).
	• Switch data (oh_switch_07272023.csv).
	• Pole data:
	  o Distribtuion HFRA Poles_08_21_23.xlsx.
	  o WORK_QUERY_FOR__BIC_AZTDINP1300.csv.
	  o WORK_QUERY_FOR__BIC_AZTDPOO2500.csv.
	• Conductor data (WORK_QUERY_FOR__BIC_AZTDPOO1400.csv)

Last Updated	Data Pull: August, 2023
Frequency of Update	Manual pull
Historic Availability	Unknown

These data sources contain information about each overhead asset type, which includes:

- Conductor (i.e., wire): contains static information such as wire distance, wire angle, wire slack and wire U-size. This wire information is collected from SPIDA pole-wire data table.
- Pole: contains static information such as pole's longitude and latitude, primary or secondary, distribution or hybrid, pole height, pole class, pole sub-type, pole base, etc. This information is gathered from the asset database and SPIDA database. The dataset includes only distribution or hybrid poles in HFRA, and excludes all secondary poles.
- Capacitor: contains static information such as manufacturer, primary voltage, system voltage, sub-type, switch-type, E-bank size, etc.
- Transformer: contains static information such as manufacturer, class, sub-type, KVA, primary voltage, secondary voltage, system voltage, etc.
- Switch: contains static information such as manufacturer, type, switch type, phase, load, main line, etc.

Incident Data

Source	Downloadable from SCE SharePoint. Contact: [redacted] for FIPA and RO data. [redacted] and [redacted] for OMS data. [redacted] for WD data. [redacted] for P2 data.
Data file(s)	• Fire investigation and pre-analysis (FIPA) data (FIPA_Database_Export_8_15_2023.csv). • Repair order (RO) data: ○ RO data (RO_Data_Export_8_15_2023.csv). ○ RO equipment data (RO_Equipment_Export_8_15_2023.csv). ○ RO event data (SharePoint_Event_Data_for_SQL.csv). • Wire down (WD) data (WD 2020 onward - 8.29.23.csv). • Outage (OMS) data (OutageData_2020_2023.csv). • Inspection and notification (P2) data (P2 Data 09132023.csv).
Last Updated	Data Pull: August, 2023
Frequency of Update	Manual pull
Historic Availability	2020 onward

We extract historical asset failures from these datasets and use them as target data to train machine learning (ML) models. Depending on the type of assets (e.g., pole or conductor) and the source of data, we apply different filters to extract SCE involved incident data from the beginning of 2020 to the end of 2022 in HFRA and for over-head distribution circuits only. Table 1 below shows how we extract target data for each asset type. Note that no asset failure has been extracted from the P2 dataset, as recommended by subject matter experts (SME).

Table 1. Extracting historical asset failures.

	FIPA	RO	WD	OMS	P2
Pole	(i) Root cause is equipment failure or construction issue. (ii) Equipment category is pole, pothead, insulator, or guy wire.	(i) Event driver is equipment failure. (ii) Equipment type is pole, cross-arm, insulator.	(i) WMP category is equipment failure. (ii) WMP sub-category is pole, cross-arm, insulator and brushing, anchor/guy. (iii) Trigger is weather, pole damaged, crossarm failure, corrosion/deterioration, insulator.	(i) RMI19 cause category is pole.	NA
Conductor	(i) Root cause is contact (CFO), conductor slap, equipment failure. (ii) Root cause spec is weather/contamination, metallic balloon, tree, foreign object, high winds, foreign contact, large sag, inconclusive. (iii) Equipment category is primary or secondary conductor.	(i) Equipment type is conductor.	(i) WMP sub-category is conductor, vegetation contact, balloon contact, wire-to-wire contact, other contact from object. (ii) Trigger is weather, vegetation, mylar balloon, damaged wire, other contact from object, connector/splice failure.	(i) RMI19 cause category is conductor/wire.	NA
Transformer	(i) Root cause is equipment failure. (ii) Root cause equipment category is transformer.	(i) Event driver is equipment failure. (ii) Equipment type is transformer.	NA	(i) RMI19 cause category is transformer.	NA
Switch	(i) Root cause is equipment failure. (ii) Root cause equipment category is switch.	(i) Event driver is equipment failure. (ii) Equipment type is switch.	NA	(i) RMI19 cause category is switch/disconnect/AR.	NA
Capacitor	(i) Root cause is equipment failure. (ii) Root cause equipment category is capacitor.	(i) Event driver is equipment failure. (ii) Equipment type is capacitor.	NA	(i) RMI19 cause category is NOT transformer, conductor/wire, pole, insulator.	NA

VEGETATION DATA

Source	Downloadable from SCE SharePoint. Contact: [redacted]

Data file(s)	• Line clearing data:
	  o Arbora line clearing data (20230926_Logic2020_LineClearing_Arbora_Insp_Mitig.csv).
	  o S123 line clearing inspection (20230926_Logic2020_LineClearing_S123_Insp.csv).
	  o S123 line clearing mitigation (20230926_Logic2020_LineClearing_S123_Mitig.csv).
	• Heavy tree data (20230926_Logic2020_HeavyTree.xlsx).
	• Structure brushing data:
	  o 20230926_Logic2020_StructureBrushing_2020.csv
	  o 20230926_Logic2020_StructureBrushing_2021.csv
	  o 20230926_Logic2020_StructureBrushing_2022.csv
	  o 20230926_Logic2020_StructureBrushing_2023.csv

Last Updated	Data Pull: September, 2023
Frequency of Update	Manual pull
Historic Availability	2020 onward

Line clearing datasets and heavy tree datasets are merged into a single dataset. All four structure brushing datasets are also merged into a single dataset. Structure brushing data is used as one feature of pole, and line clearing data is used as a feature of both pole and conductor.

The trees and their work status as well as their positions in the line clearing dataset are associated with poles and conductors based on their distances to the nearest conductor and pole (Identifying nearest pole and conductor is done as a spatial join using *geopandas* python library). A tree is considered a risk to a pole or a conductor if it is less than 10 meters away. It would be better if we could use the actual height of a tree to determine if it could hit a nearby pole or conductor. Unfortunately, missing tree height data is common in line clearing datasets, therefore we have to defer to the aforementioned assumption.

For each pole and conductor, we keep track of its number of danger trees. The higher the number, the higher the risk of failure. We reduce these numbers whenever a tree is removed or if some work has been done (e.g., trimming).

SCADA DATA

Source	Downloadable from SCE SharePoint. Contact: [redacted]
Data file(s)	• SCADA point ID to SAP equipment ID (Output_PointID_EquipmentID.csv). • List of points (Results 15,527 Points for 1066 Circuits PSPS v2.csv). • SCADA point values: 33 zip files “output*.zip” in SCADA folder on SCE SharePoint.
Last Updated	Data Pull: September, 2023
Frequency of Update	Ad-hoc
Historic Availability	Unknown

These data sources contain operational data (analog voltage, current, etc.) of capacitors and switches on over-head distribution poles in HFRAs from the eDNA and PI systems. There is no operational data available for transformers. For capacitors, available information includes voltage and delta-voltage (daily mean value and standard deviation). For switches, available information includes the current of three phase A, B, C and of the neutral and the ground. Also included are voltage of three phase A, B, C. Data is recorded every 12 hours (or every 4 hours for some equipment) or when changes happened. Data sampling rate is every 4 seconds. These reflect the historical working conditions of capacitors and switches and are used as features to predict capacitor and switch failures.

Structural Data (SPIDA)

Source	Downloadable from SCE SharePoint. Contact: [redacted]

Data file(s)	• Pole data:
	  ○ WORK_QUERY_FOR__BIC_AZTDINP1300.csv.
	  ○ WORK_QUERY_FOR__BIC_AZTDPOO2500.csv.
	• Pole inspection data (BIC_AZTD_SPSF00.csv).
	• Pole insulator data (WORK_QUERY_FOR__BIC_AZTDPOO1200.csv).
	• Pole wire data (WORK_QUERY_FOR__BIC_AZTDPOO1400.csv).
	• Pole cross-arm data (WORK_QUERY_FOR__BIC_AZTDPOO1500.csv).
	• Pole wind loading data (BIC_AZTDINP0600.csv).
	• Pole wind rating data (AZTDPOO2800.csv).
	• Pole equipment testing data (AZTDINP1000.csv).
	• Pole equipment modification data (AZTDINP1200_V2.csv).

Last Updated	Manual Pull: September, 2023
Frequency of Update	Ad-hoc
Historic Availability	Unknown
Notes	We also collect pole and conductor/wire information from this data source.

These data sources contain several datasets that provide structural information as well as test results for poles. The datasets included are described below:

- Pole master data: contains information about poles such as FLOC, latitude, longitude, pole type, class, sub-type, height, and base type.
- Pole inspection data: contains information about inspection date, flow and load case, actual result and allowable result, etc. We extract data of two flows: “SCE-PLP” and “PLP Main”; and we extract data of the following components: “Pole SF” (safety factor), “Pole strength”, “Utility guy SF”, and “Pole buckling”.
- Pole insulator data: contains information about poles’ insulators, such as number of insulators, height, type, U-size, etc. We divide insulators into different groups: “PIN”, “Deadend”, and “Clamp”. For each pole, we count the total number of insulators, as well as the numbers of insulators in each group. We use these numbers as predictors to predict pole failures.
- Pole wire data: contains information about conductors/wires. We extract conductor/wire data from this SPIDA table.
- Pole cross-arm data: contains information about poles’ cross-arms, such as configuration, height, type, U-size, etc. We divide cross-arms into four groups, based on their length. These four groups are: less than 8ft cross-arms, 8 ft cross-arms, 10 ft cross-arms, and longer than 10 ft cross-arms. We count the number of cross-arms in each group for each pole and use these numbers as predictors to predict pole failures.
- Pole wind loading data: contains information about pole wind loading tests, which includes analysis date, load case component, load case test result (passed or not passed), etc. We extract only data for the following load case components: “Pole”, “Pole strength”, “Guy 1”, and “Pole buckling”.
- Pole wind rating data: contains current wind ratings and in-service wind ratings. Only data of distribution poles and hybrid poles are extracted.
- Pole equipment testing data: contains equipment testing results (passed or not passed) of equipment on poles. We extract results for transformers, capacitors, and reclosers.
- Pole equipment modification data: contains information about conductor modifications at various poles/FLOCs. As conductors/wires at the same FLOC were replaced, we use this information to get correct characteristics of conductors/wires given a specific date and location.

Circuit and Segment Data

Source	Downloadable from SCE SharePoint. Contact: [redacted] for NET9 data. [redacted] for NET9 to iPEMS data.
Data file(s)	• Segment data (NET9_CKT.CSV). • Structure to segment to circuit mapping (NET9_SEGMENT_TO_FLOC.CSV) • NET9 segment to iPEMS segment (section) mapping (net9_with_segment_1-28-24.csv).
Last Updated	Manual Pull: September, 2023
Frequency of Update	Ad-hoc
Historic Availability	Unknown

These data sources contain circuit, segment and iPEMS segment (e.g., section) configurations. The configuration data maps each pole/FLOC (and all its equipment) to a segment, an iPEMS section, and a circuit. We use this data to aggregate probabilities of failure at the asset level to higher level, such as iPEMS segment level or circuit level. Probabilities of failure at the iPEMS segment level or circuit level are required in order to create PSPS thresholds.

Location Data

Source	Downloadable from SCE SharePoint. Contact: [redacted]
Data file(s)	• Location corrosive and flooding data (DM_ALL_STRUCS_corrosionzone.csv).
Last Updated	Unknown
Frequency of Update	Unknown
Historic Availability	Unknown

This data source contains corrosive and flooding categories for each functional location. We consider this as a static dataset, e.g., we assume corrosive and flooding categories of a FLOC do not change over time. We use this data to learn how flooding and corrosion impact poles.

INSPECTION AND MITIGATION DATA

Source	Downloadable from SCE SharePoint. Contact: [redacted]
Data file(s)	• AGP inspection data (HFRA_EQ_AGP.csv). • Other inspection data (HFRA_EQ_CIRC_IPI_ODI_EOI.csv). • Mitigation data (STG_WF_ME_INCREMENTAL.csv). • Covered conductor status data (COVERED_CONDUCTOR_SCOPE_20230705.csv)
Last Updated	Manual Pull: September, 2023
Frequency of Update	Unknown
Historic Availability	Unknown

These data sources contain inspection and mitigation data for distribution circuits in HFRAs. We use this data primarily to extract the covered conductor status for conductors, and the inspected status for poles. The assumption is if a conductor is a covered conductor, it is less likely to fail. Similarly, if a pole has been inspected, its probability of failure is lower.

Data Processing

In this section, we describe how we derive training data for different equipment types, such as pole and conductor, from the data sources above.

DATA PRE-PROCESSING

In general, for each equipment type, we first join the asset data with static data sources, such as location corrosive and flooding data or SPIDA data, based on asset locations (FLOC). This step adds more features to the asset data. Next, we join asset data with dynamic data sources, such as weather data, vegetation data, and SCADA data, based on location and date. This step associates varied weather conditions and vegetation data with assets. The last step is joining asset data with incident data of the same type, based on equipment ID and date. This final step assigns learning target label (e.g., whether an asset fails on a specific day) to each record in the asset data. Records associated with incidents are called **positive examples**, otherwise they are called **negative examples**.

After getting the asset data with static and dynamic features and learning target labels, we split it into three subsets chronologically. The first set, which contains data from the beginning of 2020 to the end of June 2022, is called the **training set**. The second set, which contains data from the beginning of July 2022 to the end of October 2022, is called the **cross-validation set**. The third set, which contains data from the beginning of November 2022 to the end of December 2022, is called the **test set**. (There are two exceptions: capacitor and transformer datasets are split on October 2022 instead of November 2022.) We choose to split the datasets on these dates to have an approximately equal number of failures on each set for all equipment types. Having too few failures on training datasets makes it difficult for the models to learn patterns from data, and having too few failures either on the cross-validation datasets or the test datasets make the models' evaluation results unreliable. Note that we decide not to use any data in 2023 since the machine learning-adjusted weather data is only available until the end of 2022.

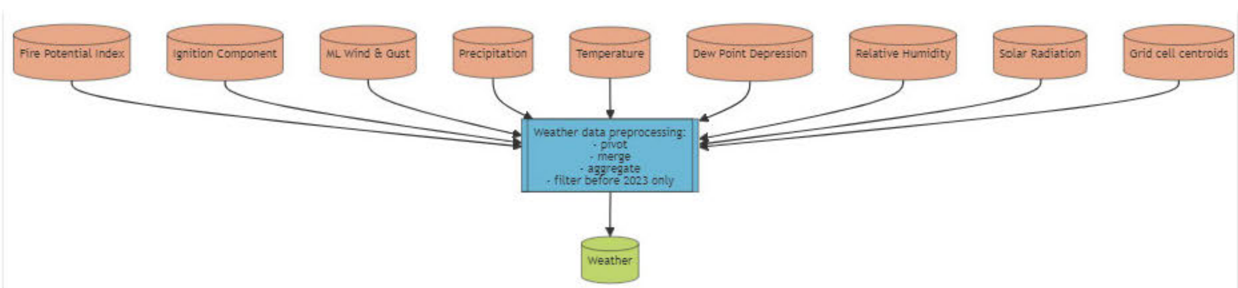
We use the training dataset to train ML models to predict equipment failures; then use the cross-validation dataset to evaluate all trained models and select the best one, based on several performance metrics. We also use the cross-validation dataset to calibrate the probabilities output by trained models. We use the test dataset to verify our best model's performance at the segment level, to create segments' probability of failure curves, and to create segments' PSPS thresholds.

For all asset types, we observe that the number of failed equipment days is very small compared to the number of normal equipment days. This makes it extremely difficult for ML models to distinguish between the failures and non-failures. To make the training process efficient and effective, we do not include all equipment in the training and cross-validation datasets. Instead, we include all equipment with failures, and a small sample of equipment with no failures. However, for the test dataset, we include all equipment so that the final segment level evaluation, the segments probability of failure curves as well as segments PSPS thresholds are non-biased.

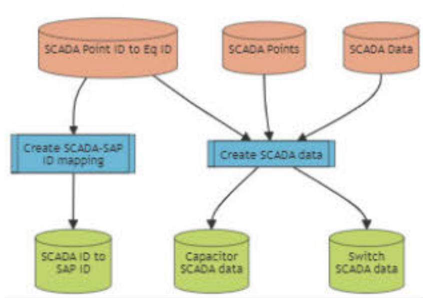
Table 2 shows statistics for datasets of all equipment types, and Figure 1,2,3, and 4 illustrate the data processing processes.

Table 2. Training data statistics.

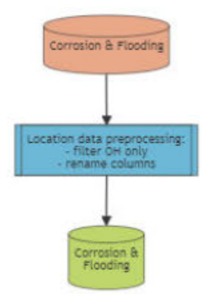
	Training dataset (Jan 2020 – June 2022)			Cross-validation dataset (July 2022 – Sept 2022)			Test dataset (Oct 2022 – Dec 2022)		
	Number of examples	Num of positive examples	Pos/Neg ratio	Number of examples	Num of positive examples	Pos/Neg ratio	Number of examples	Num of positive examples	Pos/Neg ratio
Conductor	934,620	222	0.02%	197,513	102	0.05%	15,854,492	113	N/A
Pole	853,983	89	0.01%	113,908	37	0.03%	12,160,686	28	N/A
Transformer	1,262,912	109	0.01%	117,814	107	0.09%	7,349,282	58	N/A
Switch	125,739	14	0.01%	11,993	6	0.05%	360,227	5	N/A
Capacitor	58,429	7	0.01%	5,598	3	0.05%	148,138	3	N/A



(a) Weather data processing

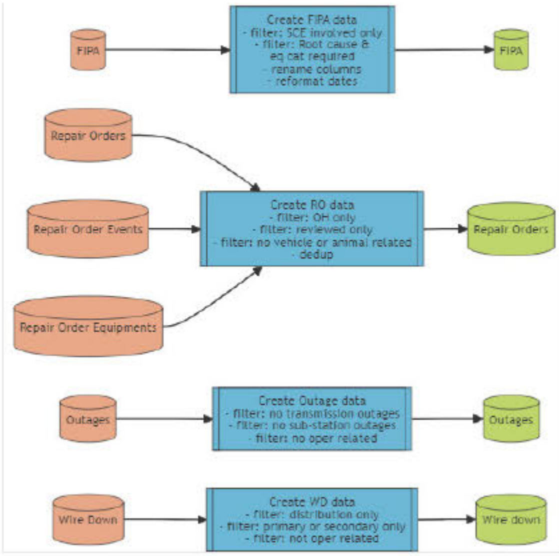


(b) SCADA data processing

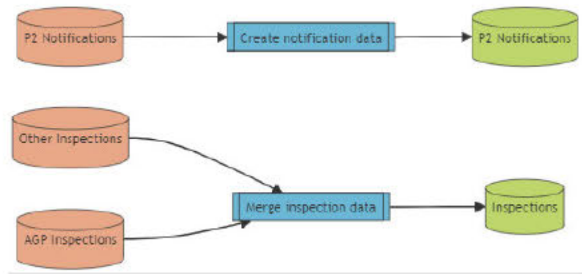


(c) Location data processing

Figure 1. Extract-Transform-Load for weather data (a), SCADA data (b), and location data (c).

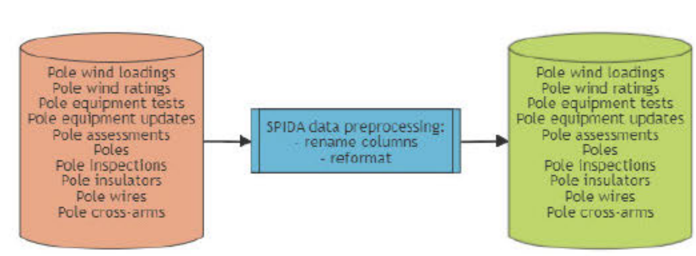


(a) Incident data processing

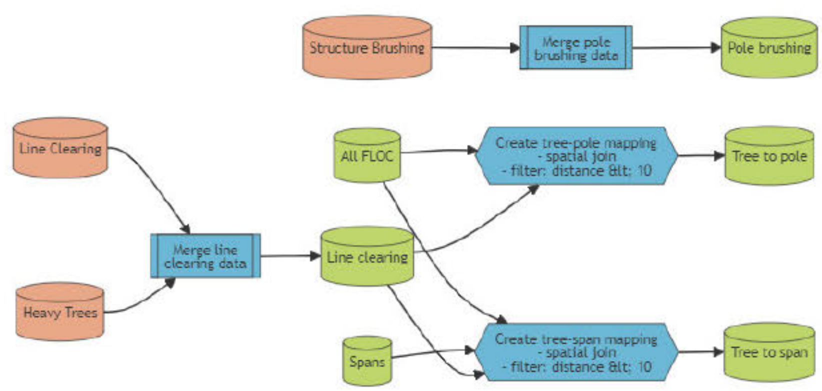


(b) Notification and Inspection data processing

Figure 2. Extract-Transform-Load for incident data (a), Notification and inspection data (b).



(a) SPIDA data processing



(b) VM data, tree-pole and tree-span mapping processing

Figure 3. Extract-Transform-Load for SPIDA data (a), Vegetation data (b and c).

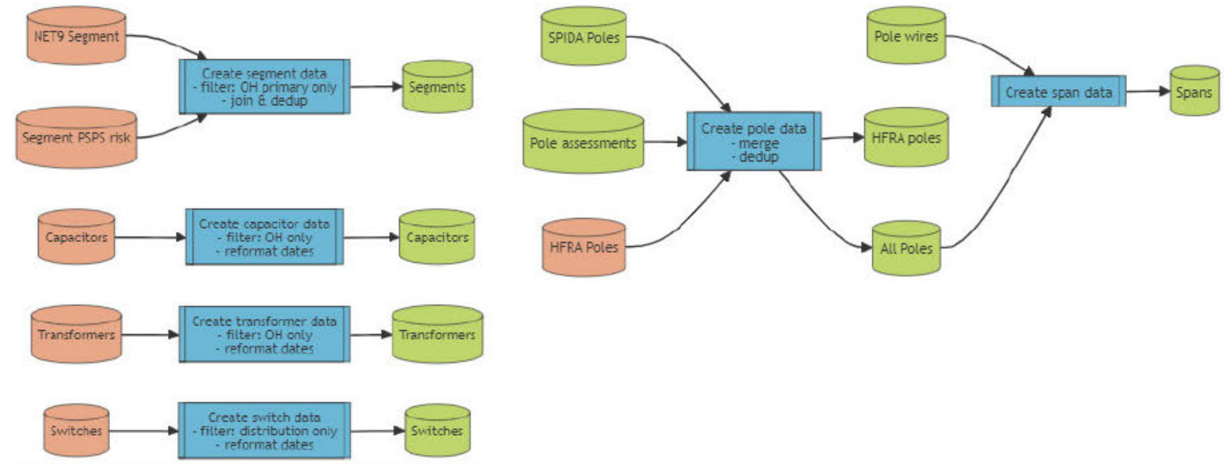


Figure 4. Extract-Transform-Load for Asset data.

CONDUCTOR TRAINING DATA

Conductor asset data contains wire distance (e.g., wire length), wire angle, wire slack, and wire size. This information is extracted from the pole-wire SPIDA table. The following are steps to derive conductor training data and are also illustrated in Figure 5:

- Join with location data to get corrosive categories and flooding categories.
- Join with weather data to get weather conditions.
- Join with mitigation data to get the covered conductor status.
- Join with vegetation data to get number of hazard trees.
- Join with conductor incident data to get learning targets.
- Calculate effective wind speed/wind gust based on wind direction, wire angle, and wire length.

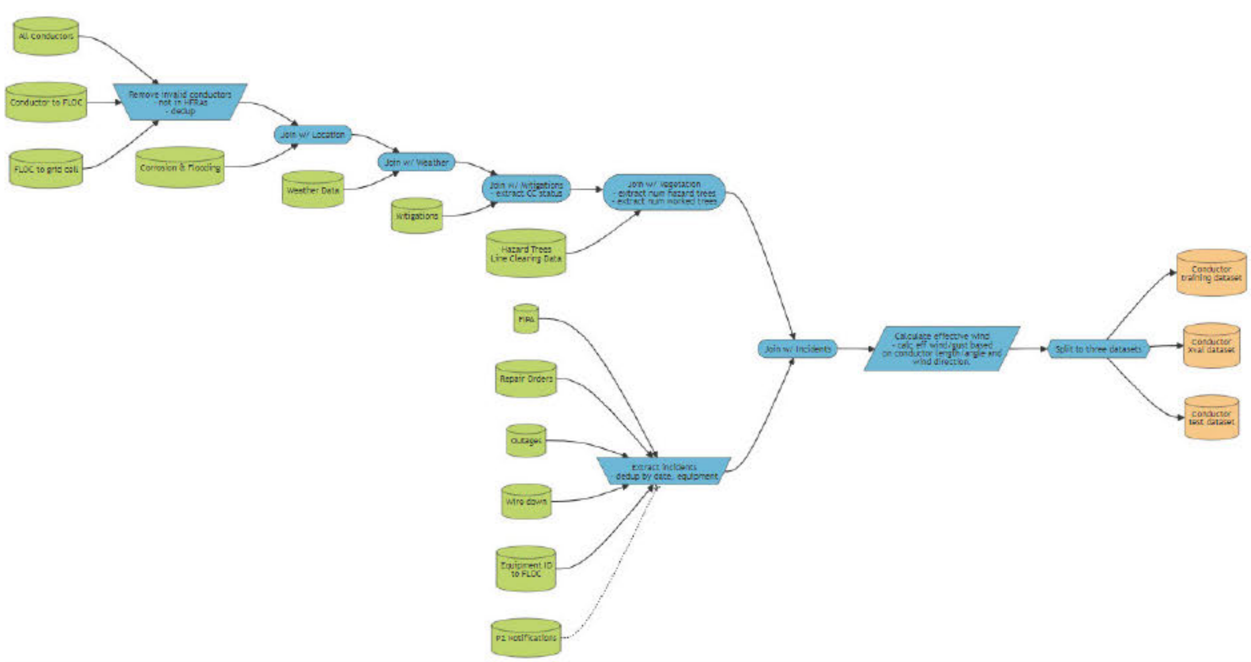


Figure 5. Deriving conductor datasets.

Pole Training Data

Pole asset data contains pole class, pole base, pole sub-type, pole height, various load and wind test results, etc. This information is extracted from multiple SPIDA tables. The following are steps to derive pole training data and are also illustrated in Figure 6:

- Join with location data to get corrosive categories and flooding categories.
- Join with SPIDA data to extract number of insulators, number of cross-arms, etc.
- Join with weather data to get weather conditions.
- Join with vegetation data to get number of hazard trees.
- Join with SPIDA pole load test data to extract test results for two flows ("SCE-PLP" and "PLP MAIN") and four components ("POLE SF", "POLE STRENGTH", "UTILITY GUY SF", and "POLE BUCKLING").
- Join with SPIDA wind load test data to extract test results for four components ("POLE", "POLE-STRENGTH", "GUY 1", and "POLE-BUCKLING").
- Join with SPIDA equipment test data to extract test results for transformer, capacitor, recloser.
- Join with pole incident data to get learning targets.

Transformer Training Data

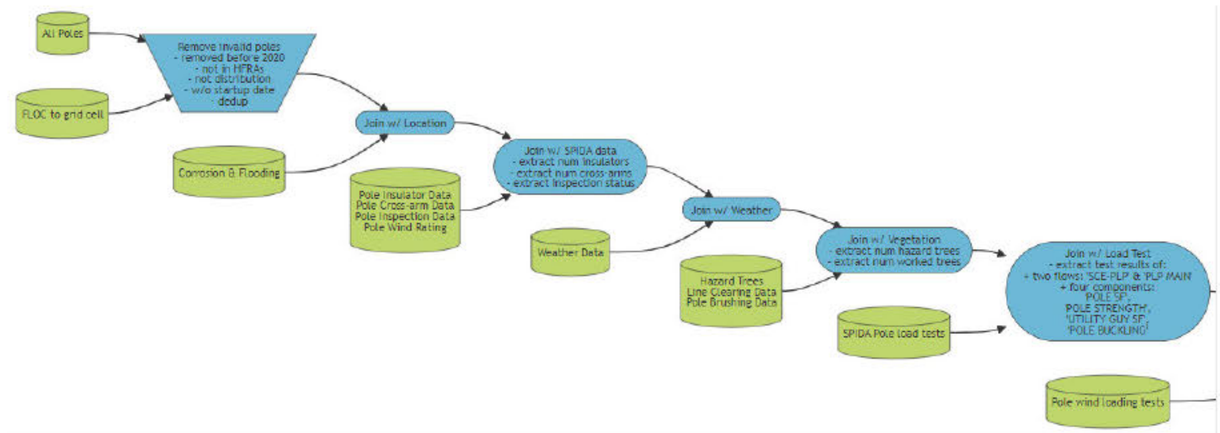
Transformer asset data contains manufacturer, sub-type, model number, primary and secondary voltages, etc. There is no SCADA data available for transformers. The following are steps to derive transformer training data and are also illustrated in Figure 7:

- Join with location data to get corrosive categories and flooding categories.
- Join with weather data to get weather conditions.
- Join with transformer incident data to get learning targets.

Switch Training Data

Switch asset data contains manufacturer, type, switch type, phase, load, DNI type, etc. SCADA data are available for switches, which includes voltage and current data of all phases. The following are steps to derive switch training data and are also illustrated in Figure 8:

- Join with location data to get corrosive categories and flooding categories.
- Join with weather data to get weather conditions.
- Join with SCADA data to get voltage and current information.
- Join with switch incident data to get learning targets.



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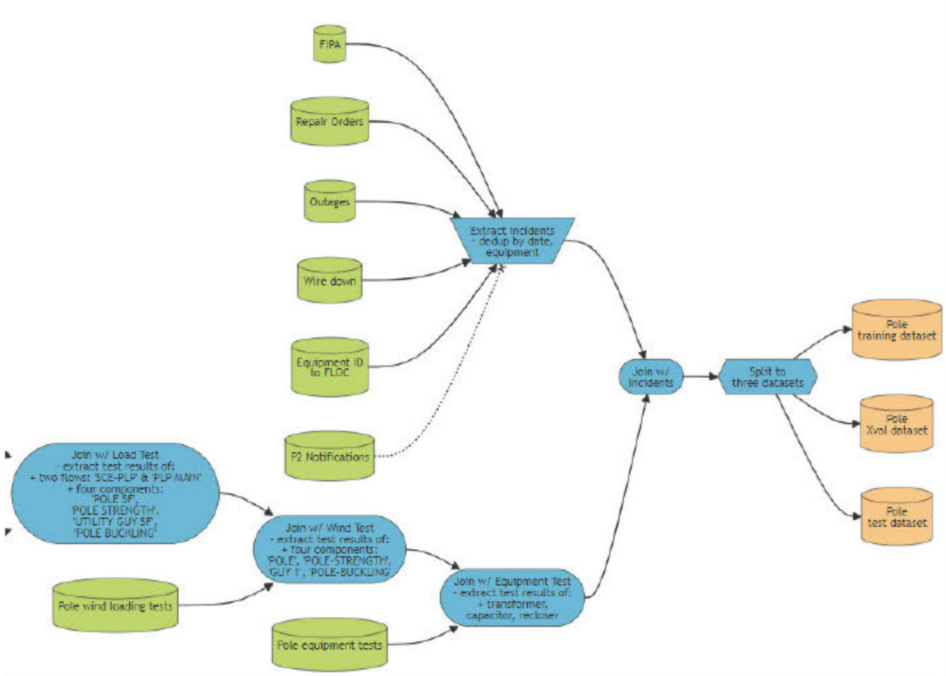


Figure 6. Deriving pole datasets.

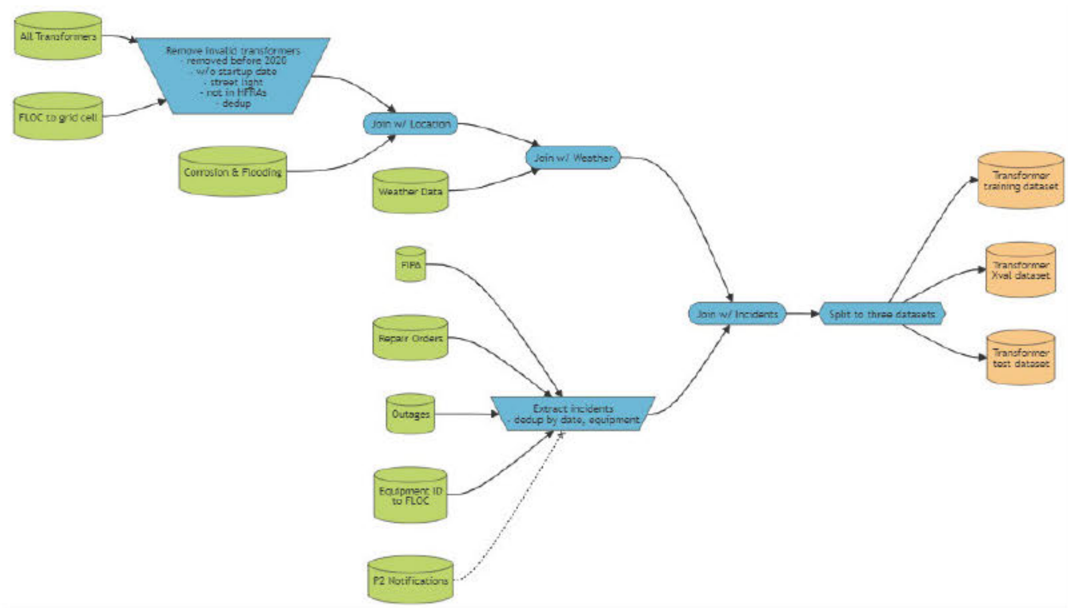


Figure 7. Creating transformer datasets.

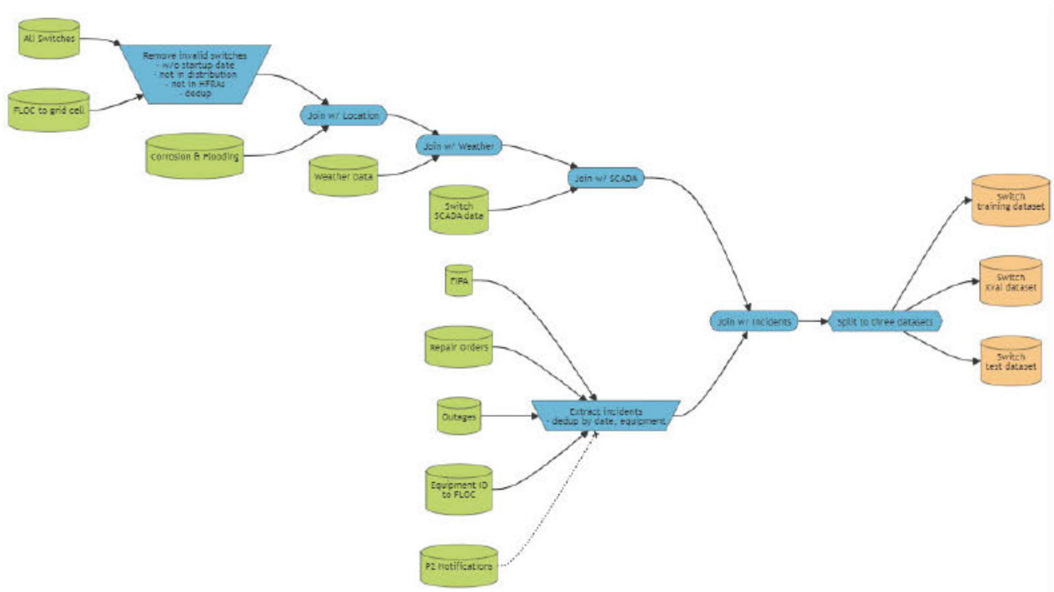


Figure 8. Creating switch datasets.

CAPACITOR TRAINING DATA

Capacitor asset data contains manufacturer, sub-type, switch type, system voltage, voltage primary, etc. SCADA data are available for capacitors, which includes voltage and delta voltage. The following are steps to derive capacitor training data and are also illustrated in Figure 9:

- Join with weather data to get weather conditions.
- Join with capacitor incident data to get learning targets.
- Join with SCADA data to get voltage and delta voltage information.
- Join with location data to get corrosive categories and flooding categories.

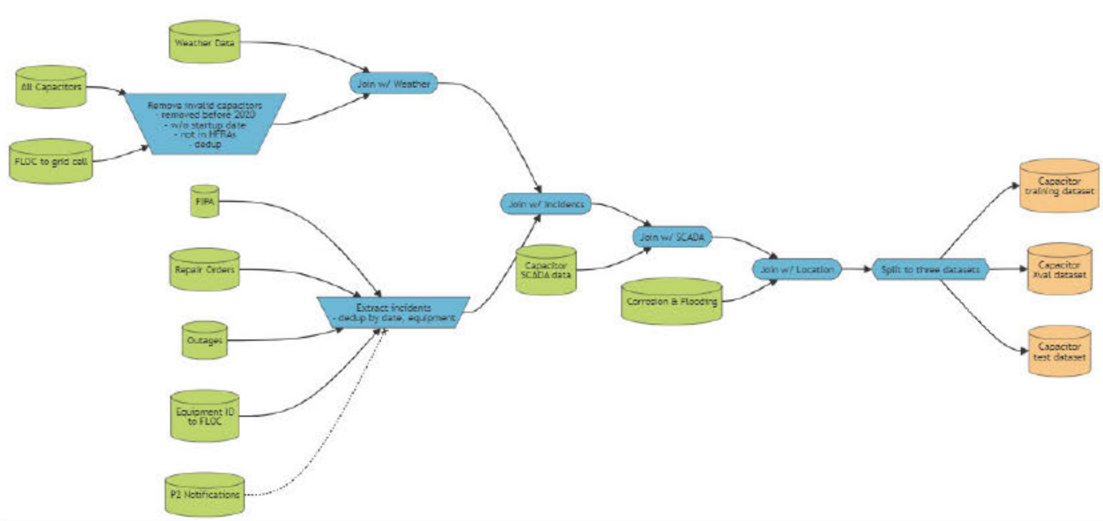


Figure 9. Creating capacitor datasets.

Model

METHODOLOGY

Given the weather conditions as well as a circuit segment and all its equipment conditions, the main question of PSPS operation is at which wind speed and wind gust equipment in the segment is likely to fail, potentially causing a catastrophic fire. Knowing the exact answer to this question helps PSPS operators to shut off power at the right time, avoiding both unnecessary PSPS and wildfire, which are costly to utility companies and their customers.

Unfortunately, there is no exact answer to the question. One can only answer it with some amount of uncertainty. In this project, we leverage historical equipment incident data and machine learning algorithms to estimate the probability of failure (POF) of assets at various wind speeds and wind gusts. To estimate the POF of segments, we aggregate POF of assets that belong to the same segment using probability laws. PSPS decision makers can use a segment POF at different wind speeds and wind gusts to estimate the risk of wildfire and to decide when to shut off power on the segment.

Our approach to probabilistically estimate PSPS wind speed and wind gust thresholds includes the following four main steps:

Training ML models to predict equipment probability of failure:

We use historical equipment incident data to train and test machine learning models to predict if a specific equipment type would fail, given the equipment characteristics and weather conditions. We train one wind speed model and one wind gust model for each equipment type (e.g., conductor, pole, transformer, switch, capacitor). These models are used to estimate the POF for each asset at various wind speeds and wind gusts. These asset level probabilities are then aggregated into segment level probabilities.

Predicting a segment probability of failure by aggregating its equipment probability of failure:

The POF of a segment is the probability at least one of its equipment fails. Given a set of equipment **e** that belong to a segment **S** and the POF of each of them, the POF of the segment is calculated as follows:

$$POF(S) = 1 - \prod_{e \in S}(1 - POF(e))$$

In the formula above, POF(S) denotes the probability of failure of a segment **S**, and POF(e) denotes the probability of failure of an equipment **e**. Obviously, the POF of segment **S** is 1 minus the probability that none of its equipment would fail, which is the product of (1 – POF(e)) for all **e** that belongs to **S,** assuming equipment are independent of one another. The formula above can also be used to calculate the POF at the circuit level.

Creating POF curves by conducting sensitivity analysis:

For each segment, we create two POF curves, one represents the segment's POF as a function of wind speed, and the other represents the segment's POF as a function of wind gust. A wind speed POF curve is created by conducting a sensitivity analysis of a POF model: all inputs to the model are fixed, except wind speed. As wind speed varies, the probability of failure predicted by the model also varies. The wind speed POF curve (i.e., function) is created from varied wind speeds as inputs and predicted probabilities as outputs. Wind gust POF curves are created similarly.

In order to conduct sensitivity analyses, we have to choose values for all fixed inputs of a model, such as temperature, or humidity. Since the wildfire consequences are significant compared to PSPS consequences, we should not underestimate the POF. Therefore, we choose to create over-estimated POF curves, by choosing values for fixed inputs so that the POF is maximal. For example, wind direction is one input of the conductor model. We choose the wind direction to be perpendicular with the conductor to maximize the wind effect.

An example of a wind speed POF curve is given in Figure 10.

Deriving PSPS thresholds from POF curves based on FPI:

PSPS thresholds can be derived from POF curves based on a pre-determined probability threshold. To account for wildfire risk, the pre-determined probability threshold is adjusted based on FPI value, e.g., we use FPI as a proxy for wildfire risk. The higher the FPI, the lower the probability threshold, and the lower the PSPS threshold. Figure 10 illustrates the use of wind speed POF curve to identify wind speed PSPS thresholds at three FPI levels, each associated with a pre-determined probability threshold.

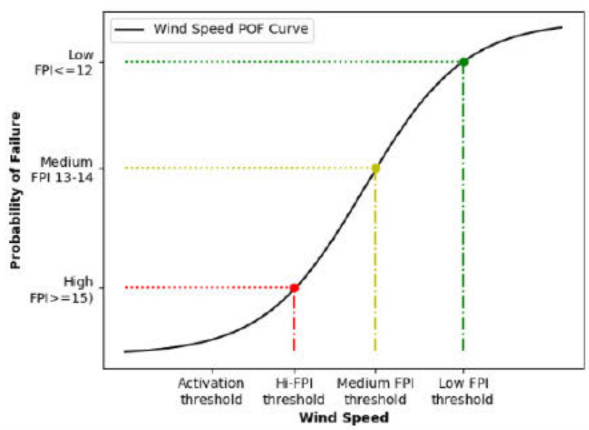


Figure 10. Determining wind speed thresholds based on FPI from wind speed POF curve.

Activation threshold of a segment is wind speed or wind gust at which PSPS operators start monitoring the segment. For a segment, activation threshold must be lower than PSPS thresholds. Activation thresholds can be derived from PSPS thresholds, simply by a striking distance.

MODEL TRAINING AND RESULTS

ASSUMPTIONS AND LIMITATIONS

We have made the following assumptions when creating training datasets, resampling training data, and deriving PSPS thresholds from segment POF curves:

- **Conductor incidents**: there is no conductor/wire ID reported for each incident, but the location and date of the incident. Therefore, for each incident, we associate it with all active conductors on that day at the reported pole/FLOC. This may create multiple conductor failures for each conductor incident reported.
- **Weather conditions associated with incidents:** weather conditions are provided for every hour. However, incidents are reported by location and date. We therefore associate the average and maximum weather conditions of a day with all incidents that occurred on that day.
- **Weather conditions associated with poles:** we assume weather conditions of a pole are the weather conditions of its nearest weather forecast grid cell (2 km by 2 km area). This might not be a good approximation for poles that are at or near the center of four grid cells. A better approximation could be a weighted sum weather conditions of four nearest grid cells, based on distance to cell centroids.
- **Weather conditions associated with conductors**: we assume weather conditions of a conductor are the same as weather conditions of its pole/FLOC. This might not be a good approximation for long conductors that span multiple grid cells. A better approximation could be a weighted sum weather conditions of all grid cells that the conductor goes through, based on distance to cell centroids.
- **Trees which are danger to poles and conductors:** most trees in danger tree data do not have their height recorded. When considering if a tree is a risk to a pole or a conductor nearby, we assume the tree height is 10 meters. That means, if the distance from the tree to a pole or a conductor is less than 10 meters, it is a danger tree as it can strike the pole or conductor.
- **Domain knowledge failure over-sampling:** one critical issue we have when training ML models is that the number of failures is diminutive. To overcome this issue, we use the following domain knowledge to create more "synthetic" failures:
    - Pole classes in order of increasing horizontal load: 10, 9, 7, 6, 5, 4, 3, 2, 1, H1, H2, H3, H4, H5, H6.
    - Pole sub-types in order of increasing strength: "WC-WESTERN CEDAR", "DOUGLAS FIR - THROUGH-BORED", "DF-DOUGLAS FIR", "CF-COMPOSITE FIBERGLASS".
    - Pole bases in order of increasing strength: "DIRT", "CEMENT"
    - Conductor size in order of increasing strength: "4 ACSR", "2 ACSR", "1/0 ACSR", "336.4 ACSR MERLIN"
- **Probability tolerance at different FPI levels:** when deriving PSPS wind speed and wind gust thresholds from POF curves, we assume the following maximum probability of failure tolerance. Adjusting these tolerance thresholds will change PSPS wind speed/wind gust thresholds accordingly, e.g., increasing tolerance thresholds will increase PSPS thresholds.
    - For high FPI (FPI >= 15): maximum POF tolerance is 20%.
    - For medium FPI (FPI = 13 or 14): maximum POF tolerance is 50%.
    - For low FPI (FPI <= 12): maximum POF tolerance is 70%.

EXPLORATORY ANALYSIS

The main goal of this study is to associate weather conditions, especially wind speed and wind gust, with equipment failures. Our hypothesis is that there is a high correlation between wind speed, wind gust, and other weather conditions, such as humidity and temperature, to equipment working status. We show below the results of several exploratory data analysis on pole and conductor data. Similar analyses on transformer, switch, and capacitor data reveal similar patterns and are omitted.

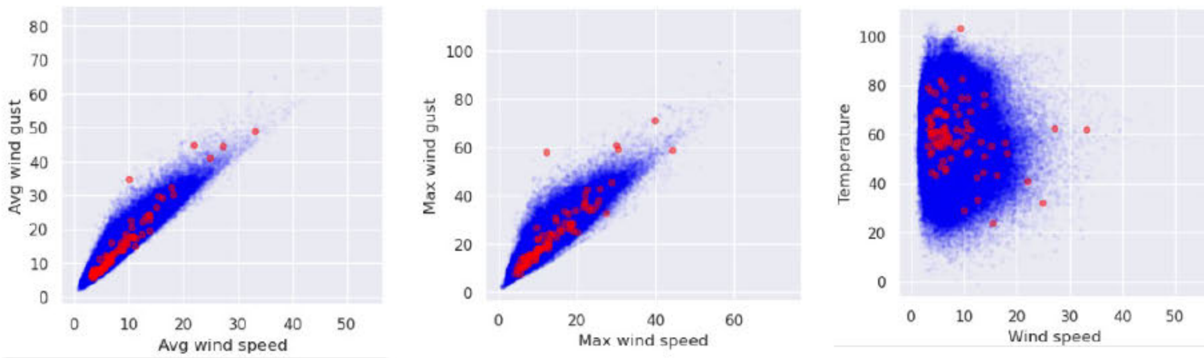


Figure 11. Pole status vs weather conditions.

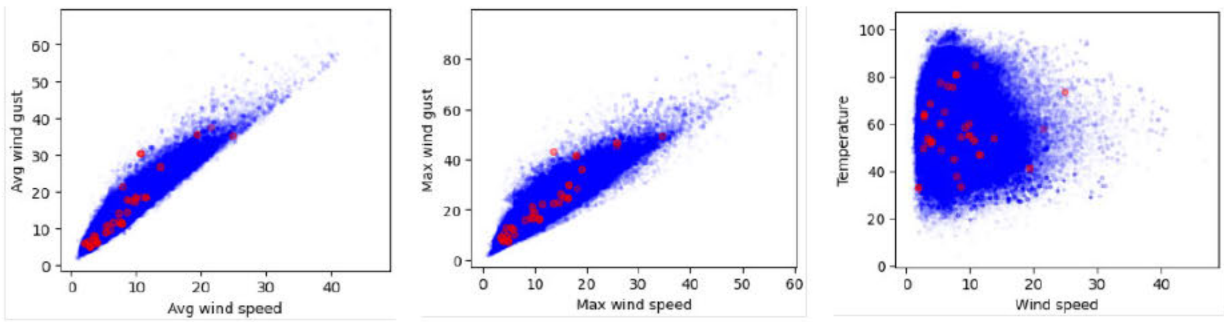


Figure 12. Conductor status vs weather conditions.

In Figure 11 and Figure 12, each equipment failure is represented by a red dot, and each normal working condition equipment-day is represented by a blue dot. We plot the working condition of poles and conductors in the training datasets against wind speed, wind gust, and temperature. It is obvious that there is no strong correlation between equipment failure and any of the weather conditions, which contradicts with our hypothesis. This suggests that training ML models to "separate" (i.e., predict) the red dots from the blue dots is hard, as they seem to be inseparable.

Feature Engineering

The diagram in Figure 13 shows all data processing we apply to training datasets to convert data to a numerical format that is understandable by ML training algorithms. Basically, for numerical data, we standardize data by removing the mean and scaling to unit variance (we use *sklearn*'s *StandardScaler* for this purpose). For categorical data, we transform data by using one-hot encoder technique (we use *sklearn*'s *OneHotEndcoder* for this purpose).

The feature engineering process is the same for all equipment types and includes the following steps:

- Remove features that have more than 30% of missing data, based on the training dataset.
- For the remaining features, fill in all missing data (for all three datasets).
    - For numerical features, use the mean values.
    - For categorical features, use "-NA-".
- For all three datasets: transform features either by standard scaling or by one-hot encoding.
    - For categorical features with many categories, to avoid over-fitting due to having only a small number of positive examples, we limit the number of categories to either 2, 3 or 5, depending on the asset type.
- Using the testing dataset to generate data for sensitivity analysis (details follow).
- Resample the training dataset to generate "synthetic" failure data for model training (details follow).

The first step above removes features with a high ratio of missing data. Table 3 lists these features for each asset type. Among all asset types, only conductor has no features removed. All SCADA features are removed from capacitor and switch datasets; and many SPIDA features are removed from pole datasets. One known issue with SCADA dataset is the lack of mapping between SCADA measurement point IDs to equipment IDs. Without this mapping, we cannot link SCADA readings to capacitors or switches. The issue with SPIDA dataset could be explained that there are only a small number of poles that have been structurally tested.

Table 3. Features removed due to high ratios of missing data.

Capacitor

Feature	*Pct data missing*
Manufacturer	92
SystemVoltage	34
VoltagePrimary	39
SwitchType	44
MountCode	73
FuseHolderType	37
FuseSize	49
NumUnits	42
LightningArrestor	32
PotentialXfrmrCld	41
Delta_Volt_Mean	77
Delta_Volt_StDev	82

Pole

Feature	*Pct data missing*	*Feature*	*Pct data missing*
elevation	90	POLE SF insp passes	99
polar_current_wind_rating	95	POLE STRENGTH_insp_passes	99
polar_inservice_wind_rating	95	UTILITY GUY SF_insp_passes	99
num_insulators	44	POLE BUCKLING_insp_passes	100
num_PIN_insulators	64	POLE_wind_load_passes	99
num CLAMP insulators	66	POLE-STRENGTH wind load passes	99
num_DEADEND_insulators	77	GUY 1_wind_load_passes	99
num_lt_8ft_Xarms	87	POLE-BUCKLING_wind_load_passes	99
num 8ft Xarms	88	TRANSFORMER test passes	100
num_10ft_Xarms	57	CAPACITOR_test_passes	100
num_gt_10ft_Xarms	97	RECLOSER_test_passes	100

Transformer

Feature	*Pct data missing*
ModelNumber	49
FLOC SystemVoltage	96
ClimateCode	75
Corrosivit	33

Switch

Feature	*Pct data missing*	*Feature*	*Pct data missing*	*Feature*	*Pct data missing*
DNIType	84	IG_Mean	96	VC_StDev	98
Manufacturer	88	IG_StDev	96	Instant.I-1_Mean	100
Load	35	IN_Mean	100	Instant.I-1_StDev	100
Corrosivit	38	IN StDev	100	Instant.I-2 Mean	100
I1_Mean	99	V2_Mean	100	Instant.I-2_StDev	100
I1_StDev	99	V2_StDev	100	Instant.I-3_Mean	100
IA_Mean	97	VA_Mean	98	Instant.I-3_StDev	100
IA StDev	97	VA StDev	98	Instant.I-G Mean	100
IB_Mean	96	VB_Mean	98	Instant.I-G_StDev	100
IB_StDev	96	VB_StDev	98	Volts_Mean	98
IC_Mean	96	VC_Mean	98	Volts_StDev	98
IC_StDev	96				

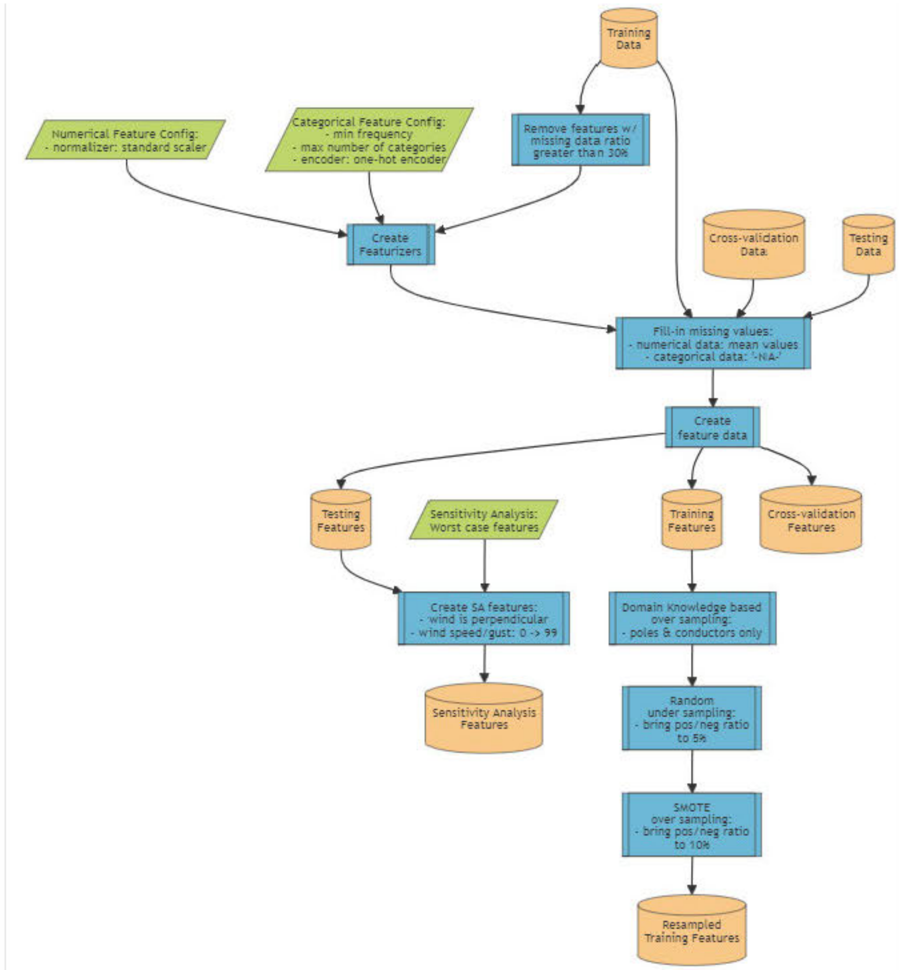


Figure 13. Feature engineering process.

Model Training and Model Selection

The diagram in Figure 14 describes our ML model training process. We train models based on the original training datasets, and based on the resampled training datasets. We use the cross-validation datasets to evaluate trained models based on a set of model performance metrics. We also use the cross-validation datasets to calibrate the probability output of the models. We rank all trained models based on a subset of metrics and select the best model that will be used to predict equipment failures.

Training algorithm: our goal is to train a model to predict if an equipment would fail given its conditions and weather conditions. This is a classic binary classification problem in machine learning, and there are many training algorithms available for it. However, there are several requirements applied to our prediction problem that limit our options.

- We want a model with a low degree of freedom (i.e., simple model) to avoid over-fitting as we don't have many positive training examples. Complex models are not appropriate as they are able to memorize positive training examples and will not generalize well on unseen data.
- We want an explainable and understandable model so that SMEs can examine and verify it. In critical applications such as our wildfire prevention application, using any of the black-box models that no one understand is risky (even if they predict well).
- We want a model that incorporates domain knowledge. For example, it should predict higher POF given higher wind speed or wind gust. This is important, as we will derive PSPS thresholds from POF curves, and only monotonically increasing curves make sense to SMEs.
- We want a model that not only predicts if an equipment would fail but also predicts it with an accurate probability. This is important because our PSPS thresholds are derived from the model prediction probabilities.

Given all requirements above, we choose to use *sklearn*'s *RidgeClassifier* training algorithm, which is similar to Logistic regression, a training algorithm commonly used for binary classification. *RidgeClassifier* is a linear model, which makes it easy to understand and explain. Being a linear model also means it has a low degree of freedom compared to other models. Most importantly, it has an option to learn only positive weights, which guarantees that the POF will be higher given higher wind speed or wind gust. This is a feature that no other available model support. Even though *RidgeClassifier* does not directly calculate the probability of its prediction, we can derive the probability using a soft-max function, as commonly used in machine learning community. Other learning algorithms, such as tree-based algorithms, support-vector based algorithms, or neural network based algorithms do not satisfy all requirements above.

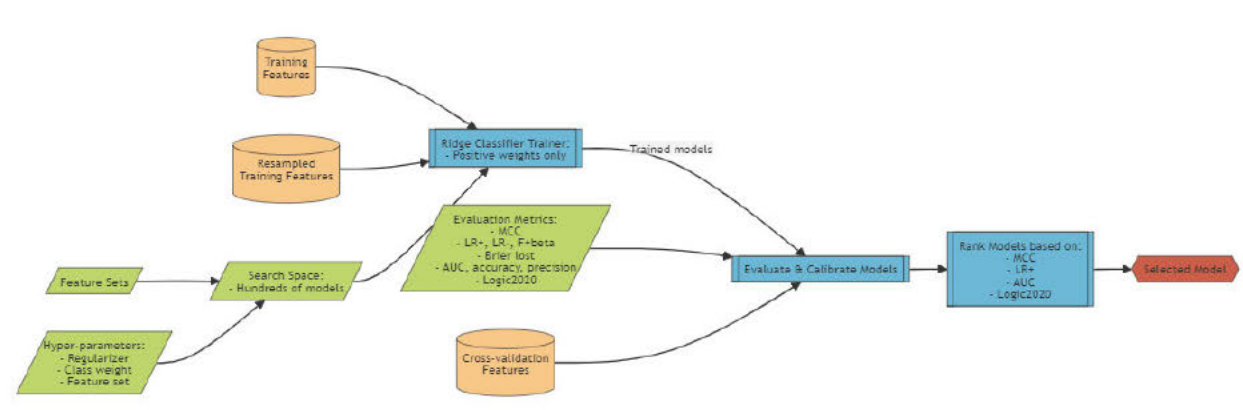


Figure 14. ML Model training process.

Constraining *RidgeClassifier* to learn only positive weights guarantees that all POF curves are strictly increasing as wind speed and wind gust increase. However, it prevents *RidgeClassifier* from assigning negative effect to categorical features, such as pole class, pole sub-type, or conductor size. For example, it is common knowledge that covered conductors are less likely to fail, compared to normal conductors. Without the positive-weight-only constraint, *RidgeClassifier* may assign a negative weight to covered conductor feature to reduce the probability of failure. Unfortunately, with the positive-weight-only constraint, the best *RidgeClassifier* can do is to assign zero weight to the cover conductor feature. This may reduce the model predictive performance.

To address the issue created by the positive-weight-only constraint, for each categorical feature, we create a new feature with the "NEG_" prefix. The values of a new feature are the negation of the values of its original feature. As a result, *RidgeClassifier* can assign a negative effect to a categorical feature by assigning a positive weight to its sibling, therefore not hurting predictive performance.

Note that we do not create "NEG_" features for any weather features, thus *RidgeClassifier* is forced to learn only positive effect on them.

Resampling: In all our datasets, the ratio of positive vs negative examples is about 0.01%. This makes it extremely hard for the training algorithm to learn any pattern in the data. We address this problem by over-sampling (i.e., synthesizing) more positive examples, and randomly under-sampling (i.e., removing) negative examples. We use two approaches to sample positive examples:

- Sampling positive examples using domain knowledge: we use our knowledge about pole and conductor strength as well as general knowledge about how wind affects equipment to generate synthetic failures.
    - Example 1: assuming there is a positive example of a class 2 pole failure. Knowing that class 2 poles are stronger than class 3, 4, and 5 poles, we can generate three more positive examples by making three exact copies of the original failure and replacing the pole class with 3, 4 and 5. The same approach can be applied to pole sub-type (knowing that "DF-DOUGLAS FIR" is stronger than "WC-WESTERN CEDAR") and conductor size (knowing that "336.4 ACSR MERLIN" size is stronger than "'1/0 ACSR", "2 ACSR", and "4 ACSR" size).
    - Example 2: assuming there is a positive example of an equipment failure at wind speed of 10 mph. Applying general knowledge, we can conclude that the same equipment would also fail at any wind speed greater than 10 mph. Therefore, we can generate more positive examples by making exact copies of the original record and replacing wind speed or wind gust with higher values.
- Sampling positive examples using SMOTE (Synthetic Minority Over-sampling Technique): SMOTE is a set of techniques commonly used by machine learning community to over-sampling the minority class. It generates positive examples by sampling the linear space between similar positive examples. SMOTE generates more data by interpolating, while our domain knowledge-based over-sampling generates more data by extrapolating. We use SMOTE in combination with our domain knowledge-based over-sampling, as the last step to bring the positive/negative ratio to 10% for all training datasets.

Note that we only resample the training datasets. We do not resample the cross-validation datasets, nor the testing datasets so that the model evaluation is not impacted by the synthetic examples.

It turns out that, out of ten of our best POF models, seven are trained on resampled datasets. However, we have not done any study to understand if the improvements are significant, and if the improvements are results of using domain knowledge resampling or SMOTE resampling.

Search space: as common practice, we use grid search approach to tune model's hyper parameters. Our search space is defined by the feature sets (combinations of different groups of features, such as weather features, asset features, SCADA features, etc.), the regularization constant, and the class weights. For each asset type, the search space normally contains hundreds of models. We train all of them using the training datasets, then evaluate them using the cross-validation datasets. Finally, we select the best model among them based on several criteria.

Evaluation metrics: each trained model is evaluated based on a set of metrics for binary classification problem. In addition, we also evaluate each model on two metrics developed by Logic2020 just for this PSPS threshold project, which we call Logic-S and Logic-WS metrics. All metrics used to evaluate models are listed below:

- **Matthews Correlation Coefficient** (MCC): The Matthews correlation coefficient is used in machine learning as a measure of the quality of binary and multiclass classifications. It considers true and false positives and negatives and is generally regarded as a balanced measure which can be used even if the classes are of very different sizes.
- **F-beta score** (+F-beta) with beta = 10: The F-beta score is the weighted harmonic mean of precision and recall, reaching its optimal value at 1 and its worst value at 0. The beta parameter represents the ratio of recall importance to precision importance.
- **Class likelihood ratios** (LR+ and LR–): The positive likelihood ratio is LR+, and the negative likelihood ratio is LR-. Both class likelihood ratios can be used to obtain post-test probabilities given a pre-test probability.
- **Brier loss score** (Brier loss): The smaller the Brier score loss, the better, hence the naming with "loss". The Brier score measures the mean squared difference between the predicted probability and the actual outcome.
- **Balanced accuracy score** (Bal Acc.): The balanced accuracy in binary and multiclass classification problems to deal with imbalanced datasets. It is defined as the average recall obtained in each class.
- **Area under the receiver operating characteristic curve** (ROC AUC): summarizes the ROC curve by computing the area under it. By doing so, the curve information is summarized in one number.
- **Average precision score** (Avg Prec.): summarizes a precision-recall curve as the weighted mean of precisions achieved at each threshold, with the increase in recall from the previous threshold used as the weight.
- **Logic20/20 model variability** (Logic-S): measure the variability of a model, by computing the percentage of equipment with probabilities vary more than 5 percent point.
- **Logic20/20 model sensitivity to wind speed/gust** (Logic-WS): measure the sensitivity of a model to wind speed or wind gust, by computing the ratio between wind speed/wind gust weights and total weights.

These metrics measure different aspects of a model, and they provide good insights into the model's performance. However, no single metric can be used to select the best model. Therefore, we carefully select a subset of metrics that best represent the desired characteristics of the models as criteria used in model selection step below.

Model calibration: The RidgeClassifier predicted probabilities of failures are not the real POF. When training a model, we ask the model to rebalance the positive and negative example ratio through the class weight parameter. This distorts the real positive/negative ratio. Consequently, the model tends to predict higher probabilities. We address this issue by using the cross-validation dataset to calibrate the model, making predicted probabilities closer to real failure probabilities. We use *sklearn*'s *CalibratedClassifierCV* for this purpose. Without calibrating, predicted probabilities at segment level are high, making generated PSPS thresholds unreasonably low.

Model selection: The aforementioned metrics measure different aspects of a model, and they provide good insights into the model's performance. However, a single metric is not enough to represent the model's performance. In addition, some metrics are highly correlated to others. Using all of them to rank trained models would signify the impact of a small group of metrics. We carefully analyze the correlation among these metrics based on cross-validation datasets, and select a subset of them for model selection.

The metrics we use to rank trained models are MCC, LR+, ROC AUC, and Logic-S. MCC is known as a good metric for binary classification problem, even in cases of imbalanced data, such as in our case. LR+ measures the predictive power of a model to the positive class, which is one of our desired criteria, as we want our model to be able to identify the rare failures among the ocean of non-failures. ROC AUC measures the overall quality of a model in terms of precision and recall. Logic-S is our own metric developed just for this PSPS wind speed threshold project. As described earlier, it measures the variability of a model. In our case, it measures the sensitivity of a model to all dynamic features, which are weather conditions. We do not use Logic-WS, our second metric developed for this project, as it only measures a model sensitivity to wind speed or wind gust. Our study reveals that Logic-WS is too biased to models that have only wind speed or wind gust features.

We rank trained models by first normalizing all metric values to the range [0, 1], with 1 representing the highest metric value. Note that for the metrics we use to rank models, the higher the value, the better. We then calculate the sum of metric values and the sum of square of metric values. Models are ranked by the sum of metric values minus the sum of square of metric values and the top ranked model is selected. By doing so, we prefer models with high total metric values, and also prefer models with balanced metric values.

Model Performance

As mentioned before, we use training datasets to train models, and cross-validation datasets to evaluate, calibrate, and rank models. The top ranked model for each asset type is used to evaluate segment level model, create POF curves and derive PSPS thresholds. Below, we report performance metrics of all top ranked models for each asset type, and also report performance metrics of the segment level model. All performance results are based on cross-validation datasets.

Conductor model performance:

Figure 15a shows the wind speed conductor model performance, and Figure 15b shows the conductor wind gust model performance. For each model, we show all its weights in decreasing order of importance, the classification report, which includes precision, recall, F1-score, and support for each class. We also show all metric values (unnormalized), confusion matrix, and the ROC curve together with the AUC.

Overall, both wind speed and wind gust conductor models are better than a random-guessing model. This is clear based on the ROC curve, as it is above the diagonal line, which represents the random-guessing model. However, the predictive powers of both models are not great, as their AUC values are less than 70%.

Both models are simple models, with very small numbers of features. The features selected by these models also fit well with our domain knowledge, except that these models do not consider conductor size. However, this could be the result of not having enough failures that cover different conductor sizes.

Note that neither model catches more than 50% of the failures. Both models operate at low false positive rate and low true positive rate. This behavior can be changed by changing the failure prediction probability threshold to less than 50% to get higher true positive rate, with the consequence of higher false positive rate.

	Feature	Weight
0	NEAR-SURFACE_WIND_SPEED_-_MACHINE_LEARNING_max	0.096279
1	eff_wind_speed_S_comp_max	0.069561
2	eff_wind_speed_S_comp_max_mult_wire_distance	0.053782
3	NEAR-SURFACE_WIND_SPEED_-_MACHINE_LEARNING_avg	0.000000
4	eff_wind_speed_S_comp_avg	0.000000
5	eff_wind_speed_S_comp_avg_mult_wire_distance	0.000000
6	INTERCEPT	-0.130094

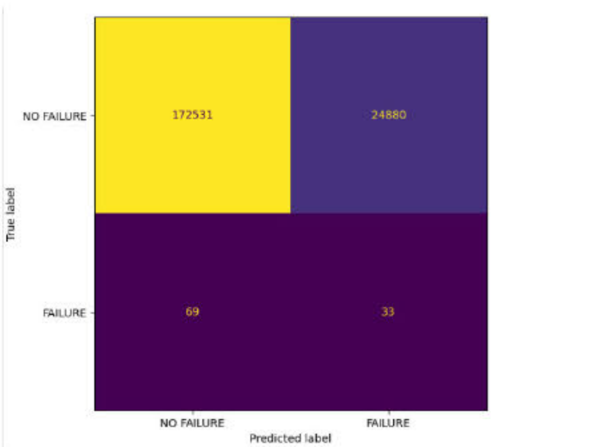
(a) Model weights

	precision	recall	f1-score	support
NO FAILURE	1.00	0.87	0.93	197411
FAILURE	0.00	0.32	0.00	102
accuracy			0.87	197513
macro avg	0.50	0.60	0.47	197513
weighted avg	1.00	0.87	0.93	197513

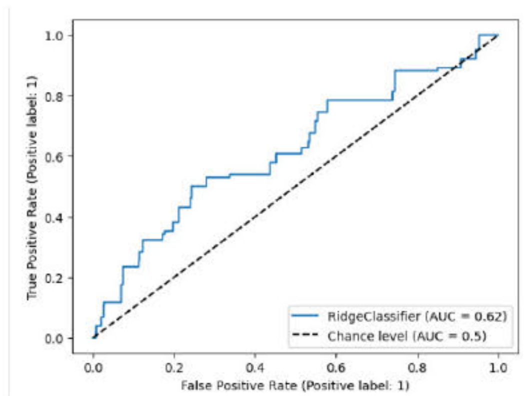
(b) Classification report

+F-beta	Avg Prec.	Bal Acc.	Brier Loss	LR+	LR-	Logic-S	Logic-WS	MCC	ROC AUC
0.0949	0.001	0.5987	0.2152	2.5671	0.774	0.9077	1.0754	0.0135	0.6199

(c) Model metric values



(d) Confusion matrix



(e) ROC AUC

Figure 15a. Conductor wind speed model.

	Feature	Weight
0	NEAR-SURFACE_WIND_GUST_-_MACHINE_LEARNING_max	0.118009
1	eff_wind_gust_S_comp_max	0.074485
2	eff_wind_gust_S_comp_max_mult_wire_distance	0.057896
3	INTERCEPT	-0.168407

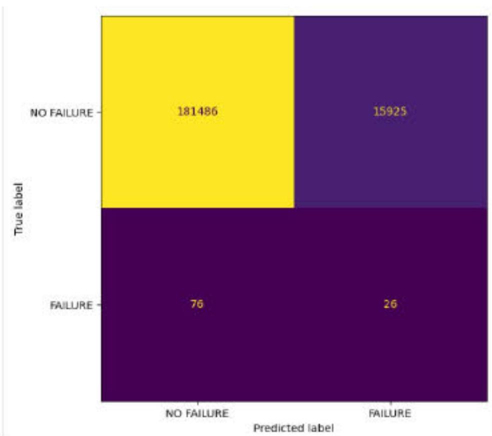
(a) Model weights

	precision	recall	f1-score	support
NO FAILURE	1.00	0.92	0.96	197411
FAILURE	0.00	0.25	0.00	102
accuracy			0.92	197513
macro avg	0.50	0.59	0.48	197513
weighted avg	1.00	0.92	0.96	197513

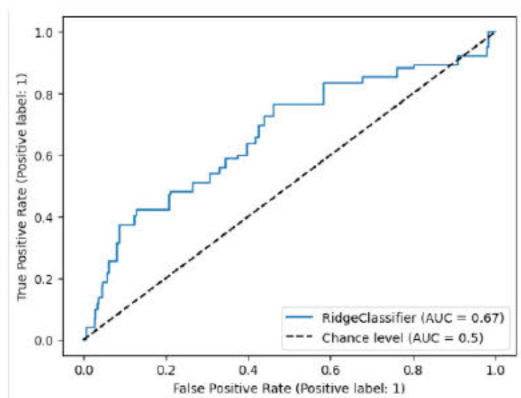
(b) Classification report

+F-beta	Avg Prec.	Bal Acc.	Brier Loss	LR+	LR-	Logic-S	Logic-WS	MCC	ROC AUC
0.1004	0.0013	0.5871	0.2042	3.1598	0.8105	0.958	1.4394	0.0145	0.6662

(c) Model metric values



(d) Confusion matrix



(e) ROC AUC

Figure 15b. Conductor wind gust model.

Pole model performance:

Figure 16a shows the wind speed pole model performance, and Figure 16b shows the pole wind gust model performance.

Similar to conductor models, both wind speed and wind gust pole models are better than a random-guessing model, as their ROC curves are above the diagonal line, and their AUC values are greater than 50%. Again, the predictive powers of both models are not great, as their AUC values are just a little higher than 60%.

Both pole models are rather complex, including many static pole characteristics such as pole base, pole class, and pole sub-type. In addition, the weight importance seems to contradict our knowledge. For example, weight importance suggests that poles with cement base are more likely to fail compared to poles with dirt base; or class 2 poles are more likely to fail compared to class 4 poles. However, it could be that there are more class 2 poles and cement base poles in the pole incident data.

Similar to conductor models, both pole models have low false positive rate and low true positive rate. We can increase true positive rate with the cost of increasing false positive rate.

Note that the number of pole failures is much smaller than the number of conductor failures, in both training dataset and cross-validation dataset (see Table 2) This makes it harder to learn a good pole model.

Feature	Weight
PoleInspected::infrequent	0.719256
pole_base::CEMENT	0.645736
pole_sub_type::DOUGLAS FIR - THROUGH-BORED	0.583675
pole_class::2	0.561730
Pri_or_sec::infrequent	0.419380
pole_class::4	0.361423
pole_base::DIRT	0.360264
pole_sub_type::DF-DOUGLAS FIR	0.273056
pole_class::infrequent	0.199922
Pri_or_sec::Primary_ONLY	0.192173
pole_sub_type::WC-WESTERN CEDAR	0.190569
NEAR-SURFACE_WIND_SPEED_-_MACHINE_LEARNING_max	0.179709
pole_class::5	0.171883
AIR_RELATIVE_HUMIDITY_2M_max	0.170450
pole_class::3	0.113606
Brushed::0.00	0.090451
ACCUMULATED_PRECIPITATION_max	0.052820
Num_Danger_Trees_Remain	0.045408
pole_height	0.043848
pole_sub_type::UN-UNKNOWN	0.041131
DEW_POINT_DEPRESSION_2M_AGL_avg	0.032975
pole_sub_type::infrequent	0.001477
ACCUMULATED_PRECIPITATION_avg	0.001358
AIR_RELATIVE_HUMIDITY_2M_avg	0.000000
DEW_POINT_DEPRESSION_2M_AGL_max	0.000000
NEAR-SURFACE_WIND_SPEED_-_MACHINE_LEARNING_avg	0.000000
SNOWFALL_WATER_EQUIVALENT_max	0.000000
SNOWFALL_WATER_EQUIVALENT_avg	0.000000
PoleInspected::N	0.000000
Brushed::infrequent	0.000000
pole_base::infrequent	0.000000
age	0.000000
INTERCEPT	-1.462679

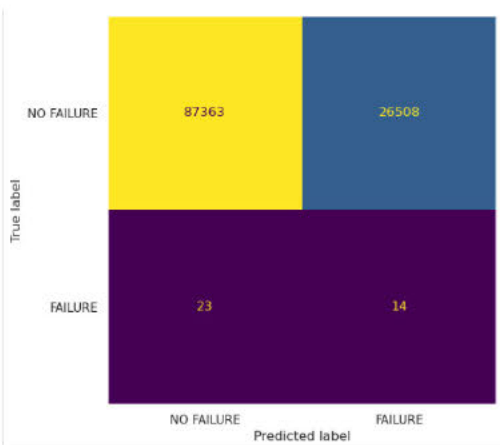
(a) Model weights

	precision	recall	f1-score	support
NO FAILURE	1.00	0.77	0.87	113871
FAILURE	0.00	0.38	0.00	37
accuracy			0.77	113908
macro avg	0.50	0.57	0.43	113908
weighted avg	1.00	0.77	0.87	113908

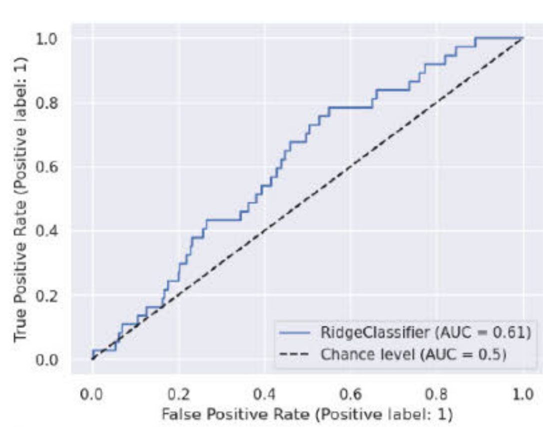
(b) Classification report

+F-beta	Avg Prec.	Bal Acc.	Brier Loss	LR+	LR-	Logic-S	Logic-WS	MCC	ROC AUC
0.0468	0.0005	0.5728	0.2081	1.6254	0.8102	0.9905	0.045	0.0062	0.6103

(c) Model metric values



(d) Confusion matrix



(e) ROC AUC

Figure 16a. Pole wind speed model.

Feature	Weight
PoleInspected::infrequent	0.737869
pole_sub_type::DOUGLAS FIR - THROUGH-BORED	0.655005
pole_base::CEMENT	0.639245
pole_class::2	0.488926
FLD_ZONE_SUBTY::infrequent	0.419027
pole_base::DIRT	0.412779
pole_class::4	0.375550
Pri_or_sec::infrequent	0.363483
pole_sub_type::DF-DOUGLAS FIR	0.311055
pole_sub_type::WC-WESTERN CEDAR	0.227837
pole_class::5	0.194773
FLD_ZONE_SUBTY::X:AREA OF MINIMAL FLOOD HAZARD	0.165272
Pri_or_sec::Primary_ONLY	0.159159
AIR_RELATIVE_HUMIDITY_2M_max	0.149129
NEAR-SURFACE_WIND_GUST_-_MACHINE_LEARNING_max	0.148002
pole_class::infrequent	0.139340
pole_class::3	0.127855
FLD_ZONE_SUBTY::D:	0.102907
Brushed::0.00	0.098055
pole_height	0.063692
Corrosivit::infrequent	0.047287
ACCUMULATED_PRECIPITATION_max	0.046387
Num_Danger_Trees_Remain	0.041827
DEW_POINT_DEPRESSION_2M_AGL_avg	0.020794
pole_sub_type::infrequent	0.020392
NEAR-SURFACE_WIND_GUST_-_MACHINE_LEARNING_avg	0.015034
AIR_RELATIVE_HUMIDITY_2M_avg	0.012929
pole_sub_type::UN-UNKNOWN	0.010935
ACCUMULATED_PRECIPITATION_avg	0.000000
SNOWFALL_WATER_EQUIVALENT_max	0.000000
SNOWFALL_WATER_EQUIVALENT_avg	0.000000
DEW_POINT_DEPRESSION_2M_AGL_max	0.000000
PoleInspected::N	0.000000
Corrosivit::Low	0.000000
Brushed::infrequent	0.000000
pole_base::infrequent	0.000000
age	0.000000
INTERCEPT	-1.691691

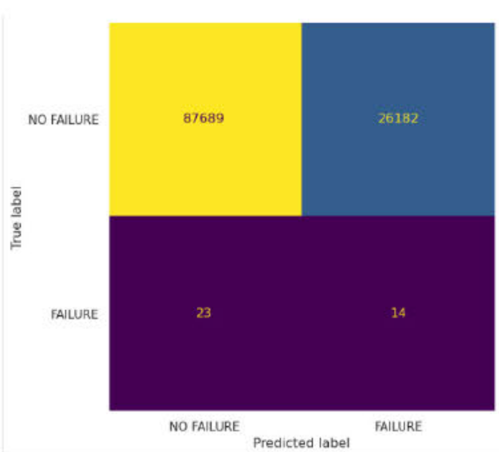
(a) Model weights

	precision	recall	f1-score	support
NO FAILURE	1.00	0.77	0.87	113871
FAILURE	0.00	0.38	0.00	37
accuracy			0.77	113908
macro avg	0.50	0.57	0.44	113908
weighted avg	1.00	0.77	0.87	113908

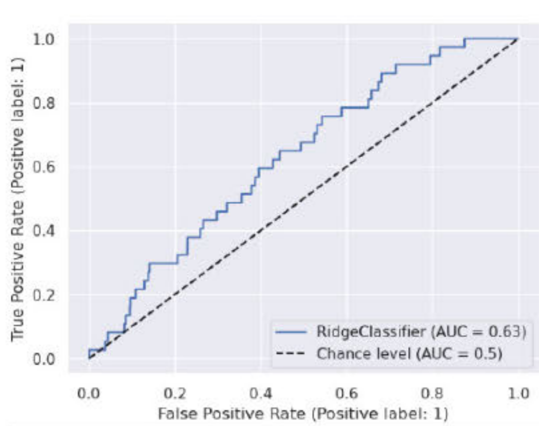
(b) Classification report

+F-beta	Avg Prec.	Bal Acc.	Brier Loss	LR+	LR-	Logic-S	Logic-WS	MCC	ROC AUC
0.0473	0.0008	0.5742	0.209	1.6456	0.8072	0.9905	0.0362	0.0064	0.6297

(c) Model metric values



(d) Confusion matrix



(e) ROC AUC

Figure 16b. Pole wind gust model.

Transformer model performance:

Figure 17a shows the wind speed transformer model performance, and Figure 17b shows the transformer wind gust model performance.

Both models are simple, with only age, temperature, and wind speed or wind gust as features. Both models are slightly better than a random-guessing model, with AUC values approximately at 60%.

Feature	Weight
age	0.169059
TEMPERATURE_2M_AGL_avg	0.124783
TEMPERATURE_2M_AGL_max	0.114071
NEAR-SURFACE_WIND_SPEED_-_MACHINE_LEARNING_max	0.113177
NEAR-SURFACE_WIND_SPEED_-_MACHINE_LEARNING_avg	0.000000
INTERCEPT	-0.248196

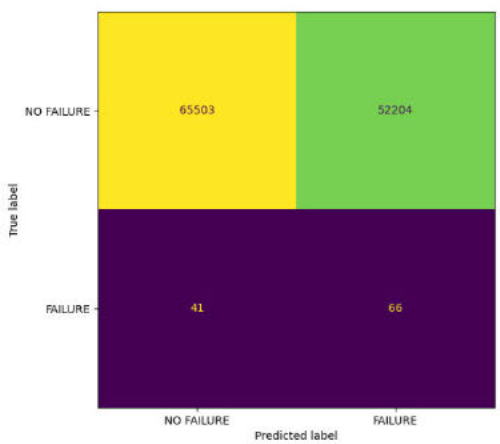
(a) Model weights

	precision	recall	f1-score	support
NO FAILURE	1.00	0.56	0.71	117707
FAILURE	0.00	0.62	0.00	107
accuracy			0.56	117814
macro avg	0.50	0.59	0.36	117814
weighted avg	1.00	0.56	0.71	117814

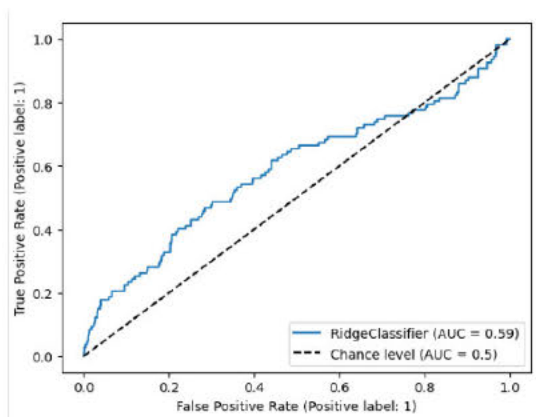
(b) Classification report

+F-beta	Avg Prec.	Bal Acc.	Brier Loss	LR+	LR-	Logic-S	Logic-WS	MCC	ROC AUC
0.1059	0.0021	0.5867	0.2479	1.3908	0.6886	0.9859	0.4147	0.0105	0.5867

(c) Model metric values



(d) Confusion matrix



(e) ROC AUC

Figure 17a. Transformer wind speed model.

Feature	Weight
age	0.161539
NEAR-SURFACE_WIND_GUST_-_MACHINE_LEARNING_max	0.133780
TEMPERATURE_2M_AGL_avg	0.129735
TEMPERATURE_2M_AGL_max	0.119182
NEAR-SURFACE_WIND_GUST_-_MACHINE_LEARNING_avg	0.000000
INTERCEPT	-0.240780

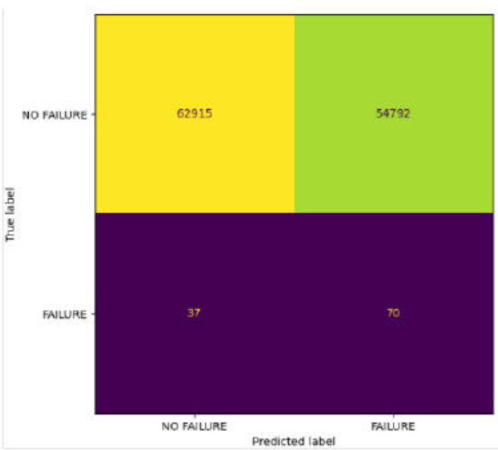
(a) Model weights

	precision	recall	f1-score	support
NO FAILURE	1.00	0.53	0.70	117707
FAILURE	0.00	0.65	0.00	107
accuracy			0.53	117814
macro avg	0.50	0.59	0.35	117814
weighted avg	1.00	0.53	0.70	117814

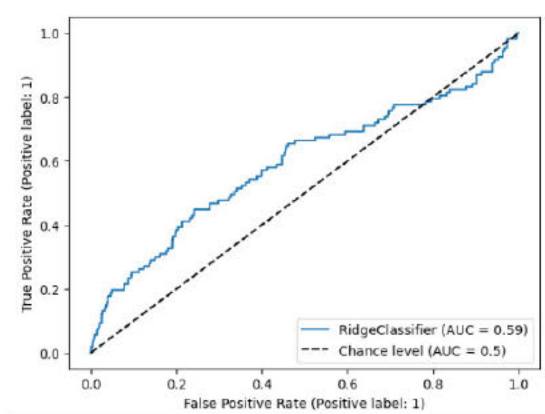
(b) Classification report

+F-beta	Avg Prec.	Bal Acc.	Brier Loss	LR+	LR-	Logic-S	Logic-WS	MCC	ROC AUC
0.1078	0.0021	0.5944	0.2506	1.4054	0.6469	0.9874	0.4409	0.0114	0.5927

(c) Model metric values



(d) Confusion matrix



(e) ROC AUC

Figure 17b. Transformer wind gust model.

Switch model performance:

Figure 18a shows the wind speed switch model performance, and Figure 18b shows the switch wind gust model performance. Both models are moderately complex, with more than a dozen features. Both models are better than a random-guessing model, with AUC values approximately at 68%, which is better than the transformer models. However, notice that there are only six switch failures in the cross-validation dataset. This makes the switch model performance result unreliable.

Feature	Weight
SwitchType::infrequent	0.764990
MainLine::YES	0.482162
NormalStatus::CLOSED	0.419044
SwitchType::POLE SWITCH	0.414280
Phase::ABC	0.334684
Type::OMN	0.323949
DOWNWARD_SHORTWAVE_FLUX_SURFACE_avg	0.251274
age	0.194036
Phase::infrequent	0.112421
NEAR-SURFACE_WIND_SPEED_-_MACHINE_LEARNING_max	0.095350
MainLine::NO	0.071172
AIR_RELATIVE_HUMIDITY_2M_avg	0.070624
DOWNWARD_SHORTWAVE_FLUX_SURFACE_max	0.051462
NormalStatus::OPEN	0.032647
DEW_POINT_DEPRESSION_2M_AGL_avg	0.000000
AIR_RELATIVE_HUMIDITY_2M_max	0.000000
DEW_POINT_DEPRESSION_2M_AGL_max	0.000000
NEAR-SURFACE_WIND_SPEED_-_MACHINE_LEARNING_avg	0.000000
ACCUMULATED_PRECIPITATION_max	0.000000
ACCUMULATED_PRECIPITATION_avg	0.000000
SNOWFALL_WATER_EQUIVALENT_max	0.000000
SNOWFALL_WATER_EQUIVALENT_avg	0.000000
SwitchType::POLE DISCONNECT	0.000000
Type::infrequent	0.000000
INTERCEPT	-2.074194

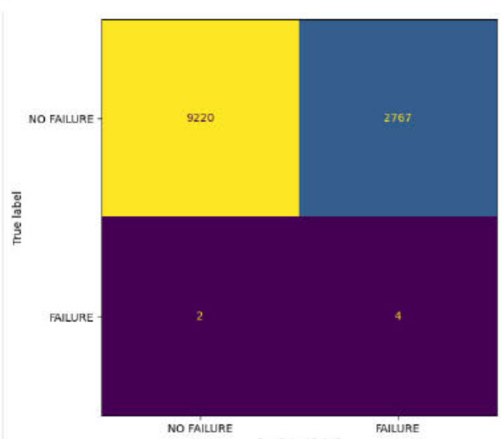
(a) Model weights

	precision	recall	f1-score	support
NO FAILURE	1.00	0.77	0.87	11987
FAILURE	0.00	0.67	0.00	6
accuracy			0.77	11993
macro avg	0.50	0.72	0.44	11993
weighted avg	1.00	0.77	0.87	11993

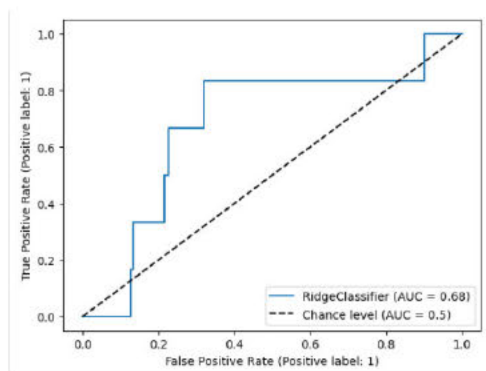
(b) Classification report

+F-beta	Avg Prec.	Bal Acc.	Brier Loss	LR+	LR-	Logic-S	Logic-WS	MCC	ROC AUC
0.1198	0.0011	0.7179	0.1693	2.8881	0.4334	0.9925	0.0618	0.0231	0.6798

(c) Model metric values



(d) Confusion matrix



(e) ROC AUC

Figure 18a. Switch wind speed model.

Feature	Weight
NEG_SwitchType::POLE DISCONNECT	0.385603
Phase::ABC	0.362106
SwitchType::infrequent	0.360761
Type::OMN	0.321224
DOWNWARD_SHORTWAVE_FLUX_SURFACE_avg	0.253645
NEG_MainLine::NO	0.220163
MainLine::YES	0.220163
age	0.179626
NEG_NormalStatus::OPEN	0.169767
NormalStatus::CLOSED	0.169767
NEG_FLD_ZONE_SUBTY::D:	0.132777
NEAR-SURFACE_WIND_GUST_-_MACHINE_LEARNING_max	0.102770
NEG_Type::infrequent	0.062301
AIR_RELATIVE_HUMIDITY_2M_avg	0.059908
DOWNWARD_SHORTWAVE_FLUX_SURFACE_max	0.057698
NEG_FLD_ZONE_SUBTY::X:AREA OF MINIMAL FLOOD HA...	0.044952
Type::infrequent	0.041542
FLD_ZONE_SUBTY::infrequent	0.033664
NEG_Type::OMN	0.028527
SwitchType::POLE SWITCH	0.024842
Phase::infrequent	0.023726
NEG_FLD_ZONE_SUBTY::infrequent	0.021554
NEG_SwitchType::POLE SWITCH	0.010182
NEG_NormalStatus::CLOSED	0.001938
NormalStatus::OPEN	0.001938
FLD_ZONE_SUBTY::X:AREA OF MINIMAL FLOOD HAZARD	0.000000
FLD_ZONE_SUBTY::D:	0.000000
DEW_POINT_DEPRESSION_2M_AGL_avg	0.000000
AIR_RELATIVE_HUMIDITY_2M_max	0.000000
DEW_POINT_DEPRESSION_2M_AGL_max	0.000000
NEAR-SURFACE_WIND_GUST_-_MACHINE_LEARNING_avg	0.000000
ACCUMULATED_PRECIPITATION_max	0.000000
ACCUMULATED_PRECIPITATION_avg	0.000000
SNOWFALL_WATER_EQUIVALENT_max	0.000000
SNOWFALL_WATER_EQUIVALENT_avg	0.000000
TEMPERATURE_2M_AGL_max	0.000000
TEMPERATURE_2M_AGL_avg	0.000000
NEG_MainLine::YES	0.000000
MainLine::NO	0.000000
NEG_Phase::infrequent	0.000000
NEG_Phase::ABC	0.000000
NEG_SwitchType::infrequent	0.000000
SwitchType::POLE DISCONNECT	0.000000
INTERCEPT	-1.122938

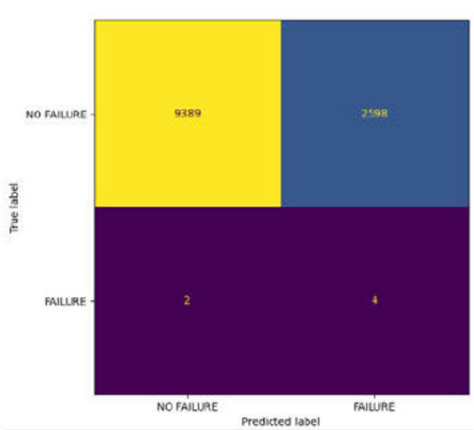
(a) Model weights

	precision	recall	f1-score	support
NO FAILURE	1.00	0.78	0.88	11987
FAILURE	0.00	0.67	0.00	6
accuracy			0.78	11993
macro avg	0.50	0.72	0.44	11993
weighted avg	1.00	0.78	0.88	11993

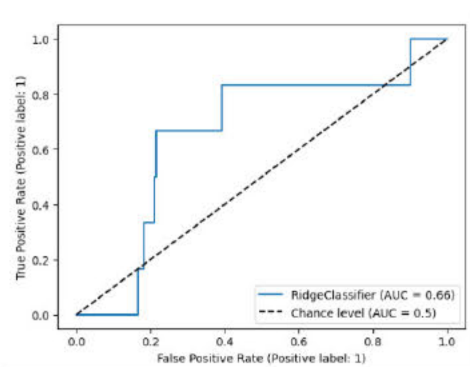
(b) Classification report

+F-beta	Avg Prec.	Bal Acc.	Brier Loss	LR+	LR-	Logic-S	Logic-WS	MCC	ROC AUC
0.1262	0.001	0.725	0.1659	3.076	0.4256	0.9925	0.0474	0.0244	0.6553

(c) Model metric values



(d) Confusion matrix



(e) ROC AUC

Figure 18b. Switch wind gust model.

Note that the switch wind gust model makes use of the "NEG_" features to assign negative effects to several categorical features, as shown in Figure 18b – section (a) above. For example, the model assigns the highest value weight to "NEG_SwitchType::POLE DISCONNECT" feature with the belief that switches of "POLE DISCONNECT" type are less likely to fail.

Capacitor model performance:

Figure 19a shows the wind speed capacitor model performance, and Figure 19b shows the capacitor wind gust model performance. Both models are simple, with only a few features. Both models are better than a random-guessing model, with AUC values approximately at 70%, which is also better than the transformer models. However, there are only three capacitor failures in the cross-validation dataset. This makes the capacitor model performance result unreliable.

Feature	Weight
AIR_RELATIVE_HUMIDITY_2M_max	0.123639
NEAR-SURFACE_WIND_SPEED_-_MACHINE_LEARNING_max	0.000000
age	0.000000
SNOWFALL_WATER_EQUIVALENT_max	0.000000
ACCUMULATED_PRECIPITATION_max	0.000000
DEW_POINT_DEPRESSION_2M_AGL_max	0.000000
INTERCEPT	-0.013326

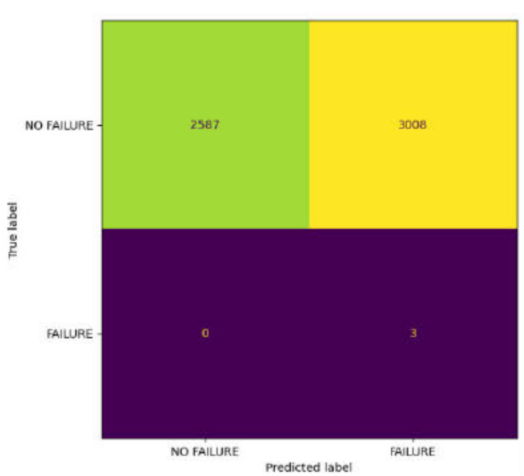
(a) Model weights

	precision	recall	f1-score	support
NO FAILURE	1.00	0.46	0.63	5595
FAILURE	0.00	1.00	0.00	3
accuracy			0.46	5598
macro avg	0.50	0.73	0.32	5598
weighted avg	1.00	0.46	0.63	5598

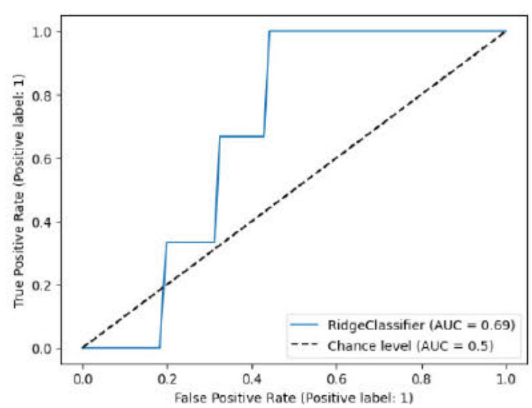
(b) Classification report

+F-beta	Avg Prec.	Bal Acc.	Brier Loss	LR+	LR-	Logic-S	Logic-WS	MCC	ROC AUC
0.0915	0.0011	0.7312	0.252	1.86	0.0	0.871	0.0	0.0215	0.6853

(c) Model metric values



(d) Confusion matrix



(e) ROC AUC

Figure 19a. Capacitor wind speed model.

Feature	Weight
age	0.228307
NEAR-SURFACE_WIND_GUST_-_MACHINE_LEARNING_max	0.132164
AIR_RELATIVE_HUMIDITY_2M_max	0.087338
SNOWFALL_WATER_EQUIVALENT_max	0.000000
ACCUMULATED_PRECIPITATION_max	0.000000
DEW_POINT_DEPRESSION_2M_AGL_max	0.000000
INTERCEPT	-0.119217

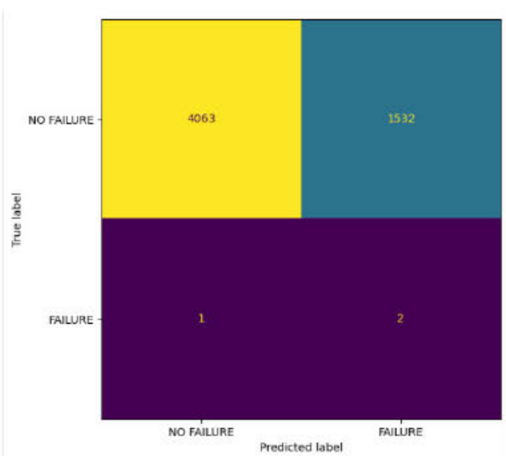
(a) Model weights

	precision	recall	f1-score	support
NO FAILURE	1.00	0.73	0.84	5595
FAILURE	0.00	0.67	0.00	3
accuracy			0.73	5598
macro avg	0.50	0.70	0.42	5598
weighted avg	1.00	0.73	0.84	5598

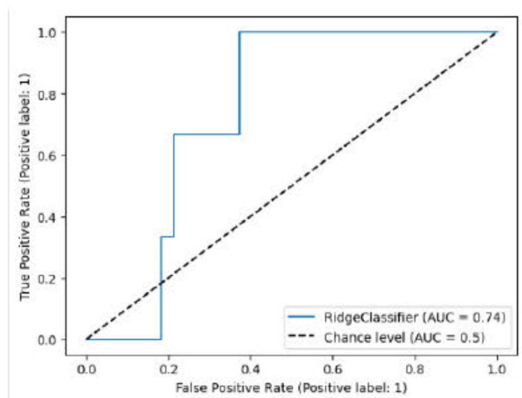
(b) Classification report

+F-beta	Avg Prec.	Bal Acc.	Brier Loss	LR+	LR-	Logic-S	Logic-WS	MCC	ROC AUC
0.1101	0.0014	0.6964	0.2289	2.4347	0.459	0.9516	0.4022	0.0204	0.7445

(c) Model metric values



(d) Confusion matrix



(e) ROC AUC

Figure 19b. Capacitor wind gust model.

Segment level model performance:

As described earlier, we calculate segment level POF based on asset level POF by aggregating them using probability laws. After consulting with SCE's SMEs, we decide to aggregate only conductor models and pole models, as they are the two main contributors to failures that cause catastrophic fire. Figure 20 illustrates the segment level evaluation process and the segment level PSPS threshold creation process.

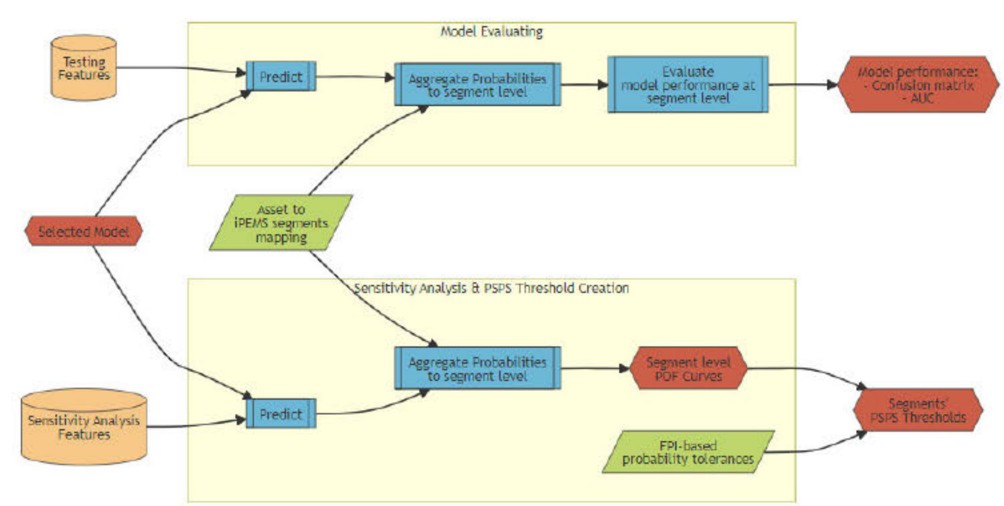


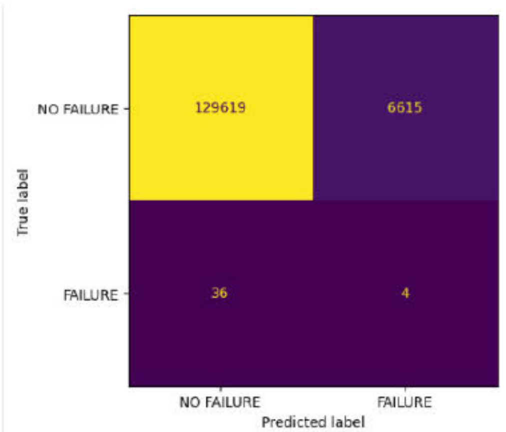
Figure 20. Segment level performance evaluation and PSPS threshold creation.

To evaluate model performance at the segment level, we use conductor and pole models to predict POF of all poles and conductors in the testing datasets, which include all poles and conductors in HFRA for the last two months of 2022. These predicted POF are aggregated by segments based on mapping data that associate each asset to an iPEMS segment. The aggregated segment level POF are used to evaluate model performance.

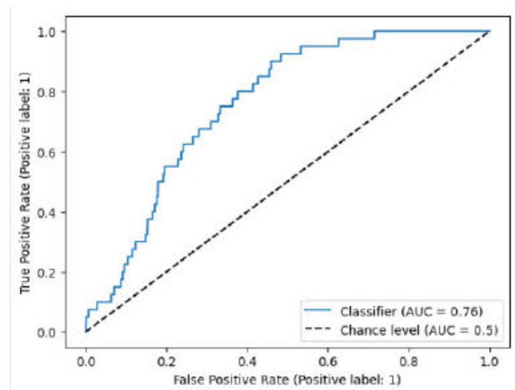
Figure 21a shows segment level performance of the wind speed model, and Figure 21b shows segment level performance of the wind gust model. Overall, both models perform much better than asset level models, as both models' AUC values are close to 80%. Both models operate at a low false positive rate and a low true positive rate, i.e., at the bottom left corner of the ROC curve. However, the steepness of both ROC curves show that true positive rate increases faster than false positive rate, which means we can effectively increase true positive rate by changing the operating point of the models up the ROC curve. For example, the wind speed model operates at 10% true positive rate, and 5% false positive rate, according to its classification report. We can change its operating point to achieve an 80% true positive rate with a 40% false positive rate, according to its ROC curve.

	precision	recall	f1-score	support
NO FAILURE	1.00	0.95	0.97	136234
FAILURE	0.00	0.10	0.00	40
accuracy			0.95	136274
macro avg	0.50	0.53	0.49	136274
weighted avg	1.00	0.95	0.97	136274

(a) Classification report



(b) Confusion matrix

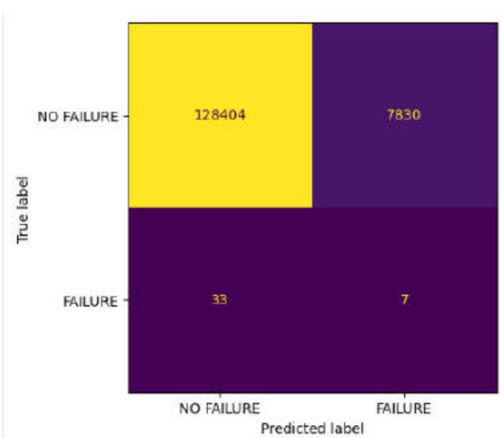


(c) ROC AUC

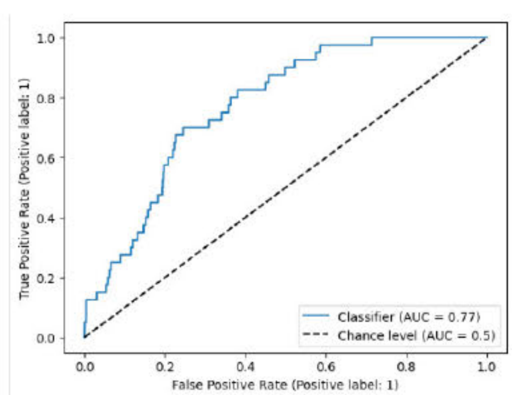
Figure 21a. Segment level wind speed model performance.

	precision	recall	f1-score	support
NO FAILURE	1.00	0.94	0.97	136234
FAILURE	0.00	0.17	0.00	40
accuracy			0.94	136274
macro avg	0.50	0.56	0.49	136274
weighted avg	1.00	0.94	0.97	136274

(a) Classification report



(b) Confusion matrix



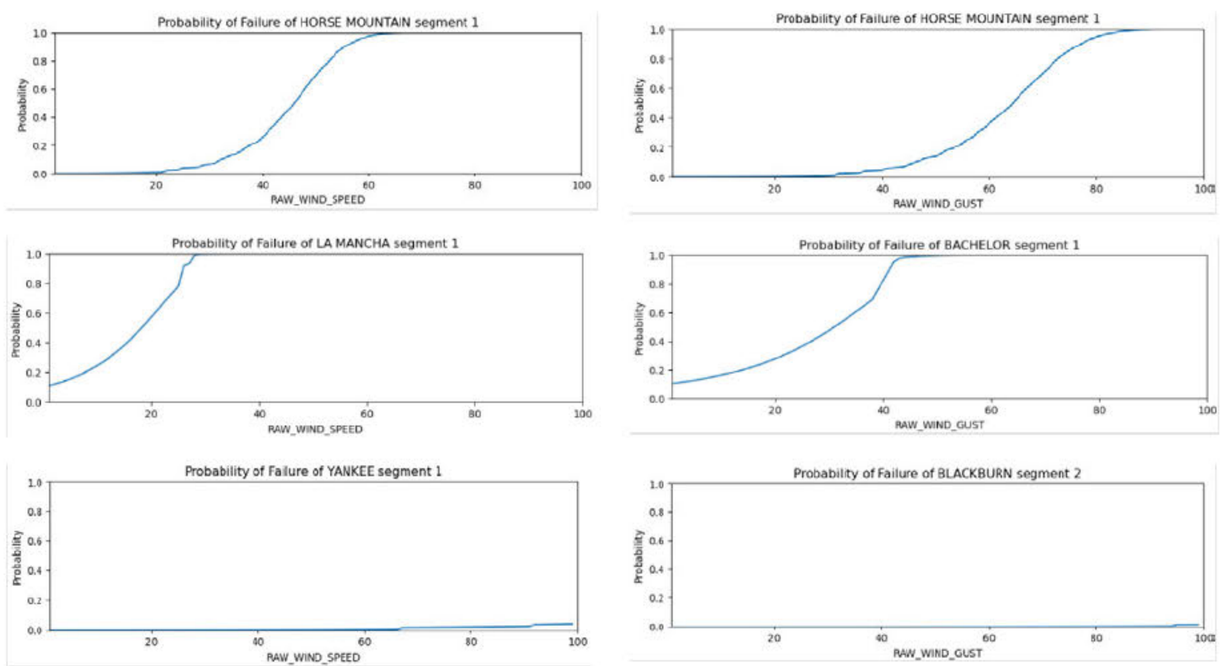
(c) ROC AUC

Figure 21b. Segment level wind gust model performance.

Creating POF Curves

The process to create segment level POF curves is similar to the model evaluation process, except that we use the sensitivity analysis dataset instead of the testing dataset, as illustrated in Figure 20. Figure 22 shows several segment level POF curves from three different groups (More POF curves are shown in Table A.4 in the Appendix.). The first group includes segments with POF curves that have wide ranges. For example, the POF curve of the circuit "Horse Mountain" segment 1 starts at probability of 0% at low wind speed and increases to 100% at high wind speed. The second group includes segments with POF curves that have narrower ranges. For example, the circuit "La Mancha" segment 1 starts out at about 10% of POF at zero mph wind speed. The third group includes segments that have curves with very little variation, normally less than 5 percent points of variation.

Segments in the third group account for only 2% to 3% of all HFRA segments. Their POF curves are neither sensitive to wind speed nor wind gust, therefore their PSPS thresholds are unreasonably high at any FPI level.



(a) Sample wind speed POF curves.

(b) Sample wind gust POF curves.

Figure 22. Sample segment level POF curves.

Deriving PSPS Thresholds

Segment PSPS wind speed thresholds are derived from wind speed POF curves, and PSPS wind gust thresholds are derived from wind gust POF curves. Thresholds are derived from POF curves based on three FPI levels: high FPI, medium FPI, and low FPI. For each FPI level, there is an associated probability tolerance level. We use 20% tolerance level for high FPI, 50% tolerance level for medium FPI, and 70% tolerance level for low FPI. That means, PSPS wind speed threshold of a segment for high FPI is the maximum wind speed at which the POF is less than or equal 20%. PSPS wind speed and wind gust thresholds at other FPI levels are derived in the same manner.

Table A.3 in the Appendix lists all PSPS wind speed and wind gust thresholds of all segments for all three FPI levels.

Conclusions

Our Methodology is Explainable, Defensible, and theoretically Deployable

This project is the result of a great collaboration among engineers, subject matter experts, and data scientists from SCE and Logic20/20. Together, we have designed and implemented an explainable, defensible and operational method to address a difficult problem of deriving PSPS wind speed and wind gust thresholds at the segment level. All models are simple, easy to understand, easy to maintain and upgrade. They are trained and evaluated based on methodologies and standards commonly used in data science and machine learning. The models can be easily deployed and operated in any cloud environments. Based on our experiments, the models can make predictions in real time.

We Follow a Data driven and Domain Knowledge Driven Approach

We've built this project based on a data driven and domain knowledge driven approach, leveraging on huge amounts of data that SCE has been recording, and on valuable knowledge from SCE subject matter experts. Both driving forces are beneficial, as large volume of data is beneficial to the model training process, while domain knowledge helps with the modeling process as well as with addressing several data issues.

Our ML Trained Models are Promising but are Not Ready for Production

The models' performances, as reported in previous sections, do not meet our expectations. For a high-risk and critical application such as the PSPS application in our case, we expect our models to have a high true-positive rate and at the same time a low false-positive rate. In other words, we expect our models to be able to predict equipment failures at high accuracy (i.e., with a small number of misses and a small number of false alarms). Failing to predict failures would lead to catastrophic wildfire, and wrong predictions of failures lead to unnecessary de-energization. Both outcomes are expensive and unwanted.

The segment level model, which is used to generate segment PSPS thresholds, has a high true negative rate of 95% (i.e., very low false alarm rate), but a low true positive rate of 10% for wind speed and 17% for wind gust (i.e., it misses a majority of historical failures). The model can be easily tuned to catch a higher number of failures, at the cost of a higher number of false alarms. As pointed out before, we can adjust the model to catch 80% of historical failures, at the cost of 40% false alarms. However, that accuracy still does not meet our expectation.

A high rate of false alarms is a result of overestimating probabilities. Over-estimated POF curves reach high values quickly, at low wind speed and wind gust level. Consequently, derived PSPS thresholds would be lower than expected. In contrast, a high rate of missed failures is a result of underestimating probabilities. Under-estimated POF curves increase slowly as wind speed and wind gust increase. In this case, derived PSPS thresholds are higher than expected (in some cases are unreasonably high). Both these types of POF curves exist, as shown in Figure 22 and in the Appendix.

Based on the models' performances, we conclude that the models we built are promising, but need further improvements and investigations in order to be in production.

There are Opportunities for Further Improvements

There are certainly opportunities for improvement that should continue to be investigated by SCE. Among them, at a high level, are improving data quality and data quantity; considering other machine learning and data handling techniques; and analyzing the generated PSPS thresholds to understand when they make sense and when they do not. We provide details in the next section.

Recommendations

ENHANCEMENTS BACKLOG

Explore other external and internal data sources: using publicly available data sources – for example the land use data source – can improve model performance by adding useful features to the training datasets. Other internal valuable data sources could also be used. For example, useful vegetation features and pole condition features could be extracted from the LiDAR data source.

Expand data scope temporally and spatially: one critical issue we have in this project is not having enough equipment failure data, especially for capacitors and switches. Expanding data scope temporally and spatially may relieve this issue. We suggest including historical data before 2020, and data of equipment not in HFRA areas. In addition, we suggest processing raw wind speed and wind gust of 2023 so we can make use of another year of data.

Improve data quality: data quality is another challenge we have, which includes missing data and invalid data. For example, many features have been removed during the feature engineering step due to high missing data rate, as reported in Table 3. In another example, about 10% of FIPA data cannot be used due to missing root cause information and root cause equipment category information. Improving data quality would definitely improve model performance as it adds more useful information to the datasets. Investing in data infrastructure such as data lake and data governance not only benefits data driven projects like this PSPS wind speed threshold project, but also benefits companywide operations.

Evaluate the effectiveness of resampling technique: based on the fact that seven out of ten selected models are trained on resampled datasets, we conclude that resampling improves models' performance. What we don't know yet are (i) whether it significantly improves performance; (ii) whether domain knowledge based over-sampling is more effective than SMOTE over-sampling or vice versa; and (iii) why resampling works for some asset and not for others. Analyses that answer these questions would help us design better resampling strategies that would lead to higher accurate models.

Experiment with other ML technologies: with higher quality data and more positive examples as the results of previous recommended enhancements, we could experiment with more complex and powerful ML training algorithms to improve models' accuracy.

Analyze and back-casting generated PSPS thresholds: even though the PSPS thresholds are generated based on moderately accurate models, it's worth knowing the difference between generated PSPS thresholds and current PSPS thresholds. Knowing that the new PSPS thresholds are similar to the current PSPS thresholds on a subset of segments will support and strengthen our knowledge; knowing that there is difference on other subset of segments might suggest further analyses that could reveal interesting findings.

Appendix

TERMS

EDA: Exploratory Data Analysis
FIPA: Fire Investigation and Pre-Analysis
FPI: Fire Potential Index
HFRA: High Fire Risk Area
iPEMS: Integrated PSPS Event Management System
ML: Machine Learning
OMS: Outage Management System
POC: Period of Concern
POF: Probability of Failure
PSPS: Public Safety Power Shutoff
RIT: Risk Informed Thresholds
RO: Repair Orders
ROC AUC: Area under the Receiver Operating Characteristic Curve
SCADA: Supervisory Control and Data Acquisition
SCE: Southern California Edison Co.
SME: Subject Matter Expert
SMOTE: Synthetic Minority Oversampling Technique
SPIDA: utility pole software solutions.
WD: Wire Down

BACK-CASTING PLAN

This is the plan to test if the PSPS thresholds derived by ML model are better than the current PSPS thresholds in use. This plan describes how to back cast PSPS wind speed thresholds. Back casting PSPS wind gust thresholds can be done in the same manner.

Back casting data: 2023 PSPS events.
Back casting methodology:

1. For a selected PSPS event, and for each activated circuit, collect the following data:
   - If the circuit was de-energized.
   - The current PSPS wind speed threshold of the circuit at the time. Call this wind speed **T0**.
   - The wind speed at which the circuit was de-energized (if it happened). Call this wind speed **T1**.
   - All after event patrol/inspection data to determine if there were critical failures, and if there was big fire.
   - Weather conditions during the period of concern (POC). Call the max wind speed during the POC **T2**.
2. Use the new model to derive PSPS wind speed threshold for the given circuit. Call this wind speed **T3**.
3. Analyze the following cases to determine if the new model's PSPS wind speed threshold is better than the current PSPS wind speed threshold, or vice versa, ignoring any circuit that has T0 = T3.
4. The new model is considered better than the current method if it is better overall.

Back casting evaluation:

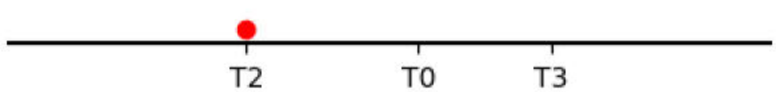
- **T0**: De-energization wind speed threshold of the circuit, identified by the current method.
- **T1**: The wind speed at which the circuit was de-energized (if it happened).
- **T2**: The max wind speed during the period-of-concern.
- **T3**: De-energization wind speed threshold of the circuit, identified by the new method.

We do not assume that whenever the wind speed exceeds the de-energization threshold T0, the circuit will be de-energized. This is based on our understanding that at SCE, during a PSPS event, the final decisions are made by the PSPS team, depending on the actual conditions of the weather and on live field observations. Case 2 and case 4 below are situations where the threshold T0 was reached but there was no de-energization.

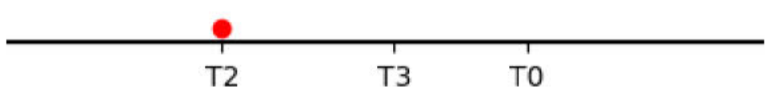
In the illustration for each case below, the red dot represents fire.

Case 1 - The circuit was not de-energized, the circuit's PSPS wind speed T0 was not breached, and there was fire: in this case, the current PSPS threshold is too high.

If T2 < T0 < T3: In this case, both methods' thresholds are too high. However, the current method is better, as its threshold is closer to T2, the wind speed at which fire happened.



If T2 < T3 < T0: In this case, both methods' thresholds are too high. However, the new method is better, as its threshold is closer to T2, the wind speed at which fire happened.



If T3 < T2 < T0: In this case, the current method's threshold is too high. Unfortunately, we can't draw any conclusion about the new method's threshold: it could be good, or it could be too low. However, since we are risk-averse, we would like to say that the new method is better, as it is able to prevent fires.

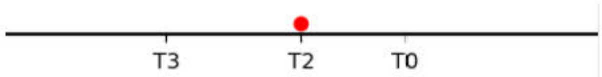
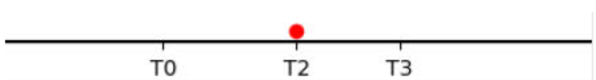


Table A.1: Circuit was not de-energized and wind speed went up to T2

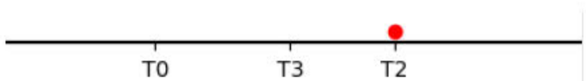
				Current Method	New Method
There was fire or significant damages	PSPS threshold was **not reached** T2 < T0	Case 1	T2 < T0 < T3	☑	✕
			T2 < T3 < T0	✕	☑
			T3 < T2 < T0	✕	☑
	PSPS threshold was **reached** T0 < T2	Case 2	T0 < T2 < T3	☑	✕
			T0, T3 < T2	Inconclusive	
There was no fire, nor significant damage	PSPS threshold was **not reached** T2 < T0	Case 3	T2 < T3, T0	Inconclusive	
			T3 < T2 < T0	Inconclusive	
	PSPS threshold was **reached** T0 < T2	Case 4	T0 < T2 < T3	Inconclusive	
			T0 < T3 < T2	✕	☑
			T3 < T0 < T2	☑	✕

Case 2: the circuit was not de-energized, the circuit's PSPS wind speed T0 was breached, and there was fire:

If T0 < T2 < T3: In this case, the new method's threshold is too high. Unfortunately, we can't draw any conclusion about the current method's threshold: it could be good, or it could be too low. However, since we are risk-averse, we would like to say that the current method is better, as it is able to prevent fires.

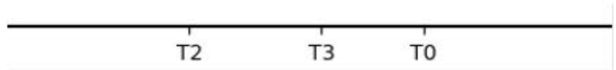


If T0, T3 < T2: In this case, we can't draw any conclusion about either method since we don't know at which wind speed the fire happened. Therefore, this case is inconclusive.

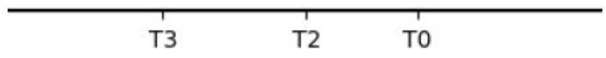


Case 3: the circuit was not de-energized, the circuit's PSPS wind speed T0 was not breached, and there was no fire:

If T2 < T0 and T2 < T3: inconclusive, as we don't know what would happen if wind speed exceeds T2.

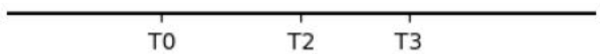


If T3 < T2 < T0: In this case, the new method's threshold is too low. Unfortunately, we can't draw any conclusion about the current method: it could be right, or it could be too high. Therefore, this case is inconclusive.

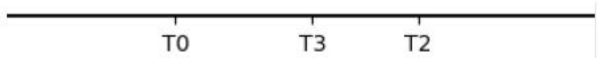


Case 4: the circuit was not de-energized, the circuit's PSPS wind speed T0 was breached, and there was no fire:

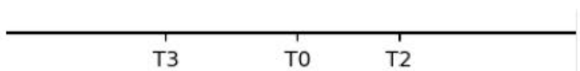
If T0 < T2 < T3: In this case, the current method's threshold is too low, but we can't draw any conclusion about the new method. Therefore, this case is inconclusive.



If T0 < T3 < T2: In this case, both methods' thresholds are too low, but clearly the new method is better as its threshold is closer to T2.

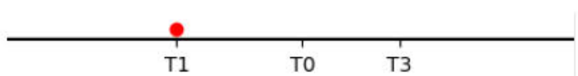


If T3 < T0 < T2: In this case, both methods' thresholds are too low, but clearly the current method is better as its threshold is closer to T2.

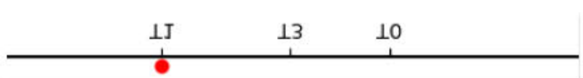


Case 5: the circuit was de-energized at T1 lower than the circuit's PSPS wind speed T0, and there was fire:

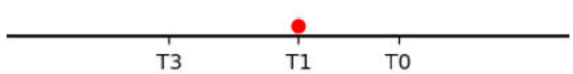
If T1 < T0 < T3: In this case, both methods' thresholds are too high, but the current method is better as its threshold is closer to T1, the wind speed at which fire happened.



If T1 < T3 < T0: In this case, both methods' thresholds are too high, but the new method is better as its threshold is closer to T1, the wind speed at which fire happened.

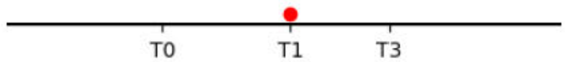


If T3 < T1 < T0: In this case, the current method's threshold is too high, but we can't draw any conclusion about the new method: it could be right, or it could be too low. However, since we are risk-averse, we would like to say that the new method is better, as it is able to prevent fires.



Case 6: the circuit was de-energized at T1 higher than the circuit's PSPS wind speed T0, and there was fire:

If T0 < T1 < T3: In this case, the new method's threshold is too high, but we can't draw any conclusion about the current method: it could be right, or it could be too low. However, since we are risk-averse, we would like to say that the current method is better, as it is able to prevent fires.



T3 < T1 and T0 < T1: In this case, we can't draw any conclusion about either method since we don't know at which wind speed the fire happened. Therefore, this case is inconclusive.

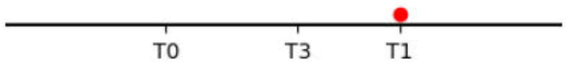
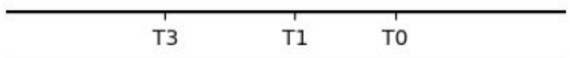


Table A.2: Circuit was de-energized at T1.

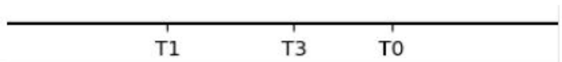
				Current Method	New Method
There was fire or significant damages	PSPS threshold was **not reached** T1 < T0	Case 5	T1 < T0 < T3	✓	✗
			T1 < T3 < T0	✗	✓
			T3 < T1 < T0	✗	✓
	PSPS threshold was **reached** T0 < T1	Case 6	T0 < T1 < T3	✓	✗
			T0, T3 < T1	Inconclusive	
There was no fire, nor significant damage	PSPS threshold was **not reached** T1 < T0	Case 7	T3 < T1 < T0	Inconclusive	
			T1 < T3, T0	Inconclusive	
	PSPS threshold was **reached** T0 < T1	Case 8	T0 < T1 < T3	Inconclusive	
			T0 < T3 < T1	✗	✓
			T3 < T0 < T1	✓	✗

Case 7: the circuit was de-energized at T1 which is lower than the circuit's PSPS wind speed T0, and there was no fire:

If T3 < T1 < T0: In this case, the new method's threshold is too low. Unfortunately, we can't draw any conclusion about the current method: it could be right, or it could be too high. Therefore, this case is inconclusive.

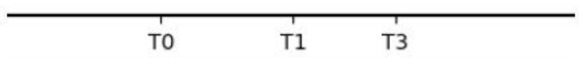


If T1 < T0 and T1 < T3: inconclusive, as we don't know what would happen if wind speed exceeds T1.

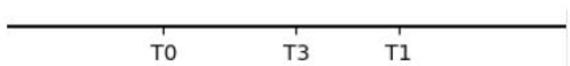


Case 8: the circuit was de-energized at T1, which is higher than the circuit's PSPS wind speed T0, and there was no fire:

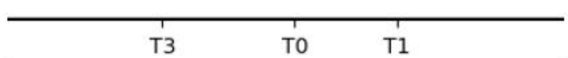
If T0 < T1 < T3: In this case, the current method's threshold is too low, but we can't draw any conclusion about the new method. Therefore, this case is inconclusive.



If T0 < T3 < T1: In this case, both methods' thresholds are too low, but clearly the new method is better as its threshold is closer to T1.



If T3 < T0 < T1: In this case, both methods' thresholds are too low, but clearly the current method is better as its threshold is closer to T1.



PSPS THRESHOLDS

Table A.3: PSPS Thresholds derived by ML model.

For segments in HFRA only.

Hi FPI probability threshold: 20%

Medium FPI probability threshold: 50%

Low FPI probability threshold: 70%

Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI		Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI	
		Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust			Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust
ABACUS	2	68	90	99	99	99	99	LEVECHE	2	43	48	54	65	62	77
ABACUS	4	28	40	38	54	43	60	LEVECHE	3	18	25	26	38	29	42
ACADEMY	1	25	36	28	41	36	51	LEXINGTON	1	12	19	24	35	27	39
ACADEMY	2	99	99	99	99	99	99	LIMITED	1	28	41	40	55	45	61
ACADEMY	3	24	35	32	46	35	51	LIMITED	2	15	24	25	37	27	39
ACADEMY	4	22	33	27	40	28	41	LIMITED	3	11	19	22	32	25	37
ACADIAN	2	20	30	26	38	30	43	LIMITED	4	28	41	37	52	41	58
ACAPULCO	1	5	11	15	24	20	30	LIMONITE	1	28	40	38	53	44	60
ACAPULCO	2	18	26	26	38	30	43	LIMONITE	4	90	99	99	99	99	99
ACCENT	1	20	30	26	38	26	38	LIVERMORE	1	25	36	33	47	38	53
ACE	1	24	34	32	45	38	52	LOCKNER	1	28	41	40	56	45	63
ACOSTA	2	34	45	44	58	49	64	LOCKNER	2	27	40	40	56	44	61
ACOSTA	3	99	99	99	99	99	99	LOPEZ	2	29	41	39	54	43	58
ACOSTA	5	99	99	99	99	99	99	LOPEZ	4	11	18	22	33	24	36
ACOSTA	6	13	20	24	35	26	38	LOPEZ	5	21	31	26	38	30	43
ACRES	1	8	14	19	28	24	35	LOTTO	1	19	24	28	40	35	46
ACRES	2	26	38	31	44	38	53	LOUCKS	1	25	35	34	48	39	55
ACRES	3	16	25	22	33	25	37	LOUCKS	2	31	44	39	55	44	61
ACROBAT	1	3	8	14	23	19	29	LOWELL	1	10	16	21	31	26	37
AGATE	1	67	86	98	99	99	99	LOWELL	2	5	9	20	29	26	37
AGATE	2	13	21	23	34	28	40	LUISENO	1	22	33	27	39	29	41
AGATE	3	20	31	27	39	28	41	LUISENO	3	1	6	11	18	15	24
AGATE	4	23	34	27	40	30	44	LUISENO	4	41	56	51	71	57	77
AGATE	5	20	30	28	40	29	42	LYONS	1	42	52	61	79	71	91
AIDAN	2	3	8	12	20	17	26	LYONS	3	1	5	11	19	16	25
ALLVIEW	1	5	7	24	30	30	37	LYTLE	2	60	77	90	99	99	99
ALPINE	1	6	8	22	27	29	37	MACIEL	2	59	78	73	96	89	99
ALPINE	2	4	5	22	28	26	35	MAGIC	1	99	99	99	99	99	99
ALPINE	3	18	23	31	41	46	57	MAHOGANY	1	83	99	99	99	99	99
ALPINE	4	11	13	26	33	33	42	MAHOGANY	2	24	35	30	43	34	49
AMBERJACK	3	88	99	99	99	99	99	MAHOGANY	3	15	23	26	37	28	41
AMBERJACK	5	26	39	34	49	38	53	MAHOGANY	4	3	7	17	26	23	33
AMBERSKY	1	99	99	99	99	99	99	MAHOGANY	5	7	14	18	28	22	33
AMBRUS	2	73	90	99	99	99	99	MAIZE	3	43	52	55	68	71	88
AMETHYST	3	29	42	40	56	45	62	MAJOR	1	48	59	60	78	73	92
AMETHYST	4	25	36	31	43	36	50	MALOY	1	15	24	23	34	26	38
ANACONDA	1	12	19	23	34	26	38	MALOY	2	78	99	99	99	99	99
ANACONDA	2	12	20	23	34	26	38	MAMBA	1	61	74	86	99	98	99
ANGUS	1	76	85	99	99	99	99	MAMBA	3	0	2	12	19	17	26
ANGUS	2	13	16	26	33	29	39	MAMBA	4	14	22	23	35	26	38
ANGUS	4	7	11	17	25	21	30	MAMBA	5	29	42	35	51	39	56
ANGUS	5	33	43	41	57	46	62	MAYER	1	1	5	11	18	15	24
ANTON	1	7	14	17	27	22	33	MAYER	2	27	39	34	49	40	56
ANTON	2	1	5	11	19	16	25	MC ALLISTER	1	59	77	68	87	80	99
ANTON	3	11	18	21	31	24	36	MCBEAN	1	24	36	29	41	35	50
ANTON	5	17	27	25	37	25	37	MCCLENNY	1	27	40	38	53	43	60
ANTON	6	32	47	41	58	46	63	MCGEE	1	5	10	28	40	39	53
ANTON	7	5	10	16	25	20	31	MCGEE	2	8	14	34	46	44	58
ANTON	8	15	23	23	34	24	36	MCLAUGHLIN	1	99	99	99	99	99	99
ANZAR	1	24	36	33	47	37	53	MCLAUGHLIN	2	24	35	30	43	34	49
APPALOUSA	1	8	15	18	27	22	33	MEADOWLARK	1	59	68	84	99	97	99
APPALOUSA	2	17	27	25	36	27	39	MEBANE	1	38	54	48	67	53	73
APPLETON	1	20	25	34	43	41	52	MEDAL	3	16	22	26	38	28	40
APPLETON	2	0	1	16	23	22	32	MEDUSA	1	15	23	25	37	27	39
ARAPAHO	1	9	16	21	32	26	39	MEMPHIS	2	11	18	21	31	25	37
ARCHIE	1	5	11	15	24	19	29	MENIFEE	3	1	5	11	19	16	25
ARCHIE	3	4	10	13	21	17	27	MENTRY	1	84	99	99	99	99	99
ARGONAUT	1	20	31	26	38	30	43	MENTRY	3	10	17	19	29	23	34
ARIEL	2	27	39	36	51	41	58	MERLIN	1	14	22	25	37	28	41
ARLINGTON	1	10	18	21	32	25	37	MERLIN	2	2	6	14	23	20	30
ARMADA	1	2	6	12	20	16	26	MERLIN	3	3	5	21	30	24	35
ARMOUR	1	13	18	27	39	30	43	MESA GRANDE	1	99	99	99	99	99	99
ARMOUR	2	11	16	24	34	27	39	MESA GRANDE	2	11	18	24	35	25	37
ASHLEY	1	1	4	15	23	21	30	METTLER	2	0	2	20	29	26	37
ATENTO	2	32	42	44	59	50	67	METTLER	3	3	8	13	21	18	27
ATENTO	3	0	0	14	20	19	28	MIDDLE ROAD	1	29	41	36	52	41	58

Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI		Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI	
		Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust			Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust
ATENTO	4	59	62	84	97	97	99	MIDDLE ROAD	4	28	41	38	53	42	59
ATENTO	5	2	5	12	20	17	27	MIDDLE ROAD	6	75	97	99	99	99	99
ATENTO	6	23	34	31	44	34	49	MIDDLE ROAD	7	29	43	38	55	42	60
ATENTO	8	49	59	74	91	86	99	MILO	1	18	27	25	37	25	37
ATENTO	9	40	54	56	76	58	80	MILO	2	3	7	15	23	20	30
ATLANTA	2	25	37	32	46	36	51	MILO	3	6	9	22	31	26	37
ATLANTA	4	25	36	32	46	37	52	MINT CANYON	2	14	22	21	31	23	34
ATMORE	1	36	51	46	64	51	70	MIRAMAR	1	6	10	18	26	23	33
ATMORE	2	15	23	25	36	27	39	MIST	1	32	46	43	59	47	65
AUTUMN	1	32	43	48	62	53	70	MIST	2	3	6	15	24	19	29
AUTUMN	2	25	35	39	54	45	62	MIST	3	31	41	52	67	55	71
AVANTI	1	77	86	99	99	99	99	MIST	4	3	6	18	26	22	32
AVANTI	3	37	52	47	65	52	71	MIST	5	19	29	27	39	31	44
AVANTI	4	28	41	37	53	42	58	MIST	6	16	24	22	32	25	37
AVANTI	5	11	14	23	32	27	38	MIST	7	23	34	30	43	35	50
AVENGER	1	16	25	26	38	26	38	MODJESKA	2	35	49	46	64	51	70
AVENGER	3	31	45	40	57	45	63	MODJESKA	3	22	32	26	38	29	43
AVENGER	4	15	23	24	35	25	37	MONACHE	1	34	48	44	61	49	68
AVENIDA	1	1	3	15	23	21	31	MONACHE	2	64	82	95	99	99	99
AVENIDA	2	30	41	41	53	47	64	MONARCH	1	3	6	15	23	21	30
AVENIDA	3	25	36	31	44	37	52	MORELAND	1	10	18	21	32	26	38
AVIATOR	1	4	10	14	23	19	29	MORELAND	2	38	45	53	66	59	74
BABYLON	1	24	36	27	39	35	50	MORELAND	3	4	9	19	29	25	37
BACHELOR	1	8	14	21	31	26	38	MORELLO	1	14	23	24	36	26	38
BACHELOR	2	13	21	24	35	27	39	MORELLO	2	10	17	19	29	23	35
BADGER	1	31	40	43	53	47	63	MORGANSTEIN	1	7	14	16	25	20	30
BADGER	2	69	72	92	99	99	99	MORGANSTEIN	10	25	37	33	48	37	53
BADGER	3	66	72	89	99	99	99	MORGANSTEIN	11	25	36	27	39	33	47
BADGER	4	50	63	76	95	88	99	MORGANSTEIN	3	16	20	41	52	52	65
BALCOM	1	19	28	25	37	26	38	MORGANSTEIN	4	10	17	20	30	25	36
BALCOM	2	7	13	18	27	22	33	MORGANSTEIN	5	65	84	95	99	99	99
BALCOM	3	7	12	21	31	24	35	MORGANSTEIN	6	61	78	87	99	99	99
BALCOM	4	12	20	19	28	22	33	MORGANSTEIN	7	12	20	22	34	27	39
BALDWIN	1	99	99	99	99	99	99	MORGANSTEIN	8	26	39	30	43	37	52
BALLOON	1	36	51	45	63	50	69	MORGANSTEIN	9	21	32	23	34	29	42
BALLOON	2	23	35	31	44	35	50	MORITZ	1	12	17	26	33	29	39
BARLEY FLATS	1	6	7	25	33	29	41	MORITZ	10	15	19	32	41	42	54
BARRINGTON	1	11	17	20	30	24	36	MORITZ	11	24	34	37	50	42	57
BARRINGTON	2	2	5	13	21	18	27	MORITZ	2	28	35	33	46	41	56
BARRINGTON	3	12	18	22	32	24	35	MORITZ	3	17	22	30	39	33	44
BARRINGTON	4	8	14	19	29	23	34	MORITZ	4	13	18	27	37	29	42
BASIL	1	21	32	27	39	28	41	MORITZ	5	26	32	42	52	58	72
BASIL	2	22	32	27	39	28	41	MORITZ	7	20	26	32	41	41	54
BATTALION	1	28	41	36	51	39	55	MORITZ	8	20	25	31	41	41	54
BAYLINER	1	20	30	27	39	31	44	MORITZ	9	15	17	27	34	39	50
BAZOOKA	1	93	99	99	99	99	99	MORONGO	1	45	62	57	78	63	84
BAZOOKA	2	99	99	99	99	99	99	MORONGO	2	0	3	10	17	14	23
BEAR VALLEY	1	10	17	18	27	21	32	MORONGO	3	5	11	15	24	20	30
BEAR VALLEY	2	10	18	19	29	23	35	MORONGO	5	3	9	13	21	17	27
BEAR VALLEY	3	15	24	24	35	26	38	MORRIE	1	97	99	99	99	99	99
BEAR VALLEY	4	99	99	99	99	99	99	MORRIS	3	93	99	99	99	99	99
BEAR VALLEY	5	17	26	22	32	25	37	MORRIS	4	24	36	30	44	37	52
BECKER	1	14	23	23	34	25	37	MT. GIVENS	1	27	37	51	68	55	71
BEECHCRAFT	2	28	41	38	53	42	59	MUDDY	1	26	37	35	50	42	58
BEELER	2	33	46	43	60	48	67	MUFFIN	1	99	99	99	99	99	99
BELPAC	1	19	29	27	40	28	41	MULHOLLAND	2	3	7	14	22	19	28
BELPAC	2	2	5	17	25	22	33	MULHOLLAND	3	15	20	28	40	33	44
BENCH	1	12	20	23	34	28	41	MUSTANG	1	24	36	32	46	36	52
BENCH	2	23	33	27	40	35	49	MUSTANG	2	22	33	28	40	34	48
BENCH	3	21	32	31	45	35	50	MUSTANG	3	12	17	24	36	27	39
BENCH	4	65	82	90	99	99	99	NAPA	1	34	49	43	60	47	66
BENCH	5	19	28	27	39	28	40	NAPA	2	10	17	19	29	21	32
BENCH	6	19	28	25	36	27	39	NAPOLEON	1	99	99	99	99	99	99
BENCH	7	99	99	99	99	99	99	NAPOLEON	2	20	30	28	40	29	42
BENCH	8	27	39	36	51	41	57	NAPOLEON	3	99	99	99	99	99	99
BENCH	9	59	76	79	99	91	99	NAPOLEON	5	19	30	27	40	28	41
BERMITE	2	99	99	99	99	99	99	NAPOLEON	6	64	83	85	99	98	99
BERMITE	3	25	36	31	45	37	51	NATIONS	1	3	8	12	20	16	26
BIANCO	2	14	23	24	35	25	37	NAVEL	1	99	99	99	99	99	99
BIDDER	1	27	39	35	49	40	57	NAVEL	2	99	99	99	99	99	99
BIDDER	2	25	36	48	64	54	72	NEAPOLITAN	2	29	41	39	54	45	61
BIDDER	3	51	65	62	81	75	96	NEARGATE	2	6	9	21	29	25	36
BIDDER	4	31	38	51	63	55	68	NEPAL	1	52	67	77	97	89	99
BIG CREEK-PORTAL	1	32	46	47	64	52	71	NEPAL	2	11	15	23	34	26	37
BIG CREEK-PORTAL	2	99	99	99	99	99	99	NERO	1	33	45	45	62	51	70
BIG CREEK-PORTAL	3	67	88	97	99	99	99	NERO	2	13	21	23	34	26	38

Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI		Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI	
		Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust			Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust
BIG CREEK-PORTAL	4	60	79	85	99	99	99	NICHOLAS	1	17	24	27	39	30	42
BIG CREEK-PORTAL	5	50	69	63	88	80	99	NICHOLAS	2	13	18	25	35	27	40
BIG CREEK-PORTAL	6	20	30	25	37	27	39	NICHOLAS	3	21	28	28	41	33	42
BIG CREEK-PORTAL	7	18	27	25	37	27	40	NICHOLAS	4	1	2	16	24	23	33
BIG FALLS	1	13	21	22	32	25	38	NICHOLAS	5	31	37	44	53	55	68
BIG ROCK	1	1	6	11	19	14	23	NICHOLAS	6	18	25	30	43	37	50
BIG ROCK	3	3	2	23	29	28	39	NICKLIN	1	99	99	99	99	99	99
BIGFOOT	1	43	54	62	81	74	97	NICOLE	1	29	43	41	58	47	64
BING	2	36	51	44	61	49	68	NIGHTHAWK	1	10	17	20	30	23	34
BING	4	99	99	99	99	99	99	NORTH SHORE	1	19	22	28	38	36	49
BING	5	28	41	36	52	41	58	NORTHPARK	1	26	38	35	50	39	55
BIRCHIM	1	19	29	26	38	32	46	NORTHPARK	2	28	35	38	51	42	56
BIRCHIM	2	16	23	36	50	44	61	NORTHPARK	3	15	22	23	34	25	36
BIRCHIM	3	28	40	49	66	57	75	NORTHPARK	4	24	32	33	44	38	51
BIRCHIM	4	13	19	27	38	34	48	NORTHPARK	5	8	8	24	35	32	41
BIRCHIM	5	99	99	99	99	99	99	NORTHPARK	7	20	27	31	42	35	48
BIRCHIM	6	50	69	69	93	72	97	NOVA	1	25	37	30	44	36	52
BLACKBIRD	2	17	26	22	33	25	37	NUTMEG	1	15	24	25	36	26	38
BLACKBIRD	3	22	33	30	44	35	50	NUTMEG	2	0	3	11	18	16	24
BLACKBURN	1	14	23	22	33	23	34	OAK GLEN	1	9	15	19	29	23	35
BLACKBURN	2	99	99	99	99	99	99	OAK GLEN	2	1	5	15	23	21	31
BLACKFOOT	1	17	26	25	37	28	40	OAK GLEN	3	24	33	38	53	45	61
BLUE CUT	1	30	43	40	56	45	62	OAK GLEN	4	5	10	19	28	25	36
BLUE CUT	2	8	16	20	31	25	37	OAK KNOLL	1	1	2	19	26	25	36
BLUE CUT	3	4	9	23	34	27	39	OAKDALE	1	27	39	35	50	39	56
BLUE CUT	4	9	16	19	29	23	34	OLIVER	1	23	34	26	38	31	44
BLUE CUT	5	6	12	17	26	21	32	OLIVER	2	25	38	32	46	37	53
BOA	1	4	10	16	24	21	31	OLIVER	3	13	19	23	34	26	37
BOBSLED	1	46	59	65	85	79	99	OMEGA	2	24	34	31	45	38	53
BOBSLED	2	36	48	50	67	55	73	OMEGA	3	10	15	23	33	26	38
BODKIN	1	99	99	99	99	99	99	OMEGA	4	30	40	46	62	51	65
BODKIN	2	29	41	43	59	49	67	OMEGA	5	7	12	25	36	28	40
BOGART	2	27	38	34	48	40	56	ONAGA	2	15	23	24	35	27	40
BOHEMIA	2	27	39	37	52	42	59	ONAGA	3	3	8	13	22	18	28
BOMBAY	2	24	36	32	45	36	51	ONBORD	1	99	99	99	99	99	99
BOMBAY	3	99	99	99	99	99	99	ONBORD	2	11	16	22	33	25	36
BONNEVILLE	1	27	40	40	56	45	61	ONBORD	3	28	41	37	53	42	59
BONNEVILLE	2	10	17	20	30	24	36	ORION	1	24	35	27	39	34	49
BONNEVILLE	3	17	25	26	38	26	39	OSLO	2	25	37	37	53	41	57
BONNIE	2	27	39	31	44	37	53	OVERLOOK	1	12	20	23	35	27	39
BOOTLEGGER	2	20	29	28	41	35	49	OWENS	2	25	37	33	47	37	52
BOOTLEGGER	4	12	16	37	49	48	61	OWENS	3	14	22	24	35	26	38
BOOTLEGGER	5	1	4	12	19	15	23	PADOVA	2	16	25	23	34	24	36
BOOTLEGGER	6	36	52	53	71	59	81	PADOVA	3	99	99	99	99	99	99
BOOTLEGGER	8	36	50	57	77	62	83	PAINTED CAVE	1	9	14	22	32	27	37
BOOTLEGGER	9	20	30	29	42	35	50	PALACE	1	16	25	25	37	27	39
BORCHARD	1	14	21	25	37	27	40	PALMER	1	13	21	24	35	26	38
BORCHARD	2	20	30	25	37	31	45	PALMER	2	17	26	23	35	27	39
BORDEAUX	2	27	40	36	52	40	57	PALMER	3	32	43	47	62	56	74
BOULDER	1	58	65	69	84	85	99	PALOMINO	1	6	11	15	24	20	30
BOULDER	3	66	88	96	99	99	99	PALOMINO	2	21	32	27	39	31	45
BOULDER	4	14	20	25	36	26	38	PANCHO	2	55	58	80	90	92	99
BOULDER	5	25	37	34	48	39	54	PAR	1	59	77	88	99	99	99
BOUQUET	2	3	7	13	21	18	27	PARADISE	1	13	18	25	37	27	39
BOUQUET	3	6	11	16	25	21	31	PARADISE	2	7	6	26	31	30	40
BOUQUET	5	22	34	32	46	36	51	PARADISE	3	9	9	22	28	25	34
BRADLEY	1	7	13	16	26	21	32	PARSONS	1	99	99	99	99	99	99
BRENNAN	1	11	19	19	29	23	34	PARSONS	2	34	48	42	59	47	65
BRENNAN	2	5	10	16	25	20	31	PASCAL	1	99	99	99	99	99	99
BRENNAN	3	52	68	68	86	83	99	PATRICIA	1	25	33	30	42	37	47
BROADCAST	1	10	17	15	23	17	25	PATRICIA	2	0	1	16	23	22	32
BROADCAST	2	16	24	20	30	23	33	PATRIOT	1	17	25	26	38	28	41
BROOKINGS	1	52	68	82	99	95	99	PATRIOT	2	1	5	13	22	19	29
BRUMFIELD	1	3	8	12	20	17	26	PAWLEY	1	3	7	18	27	23	34
BRYN MAWR	2	11	18	21	32	26	38	PAWLEY	3	2	5	14	22	18	27
BUCKBOARD	1	16	25	24	35	25	37	PAWNEE	1	14	23	24	35	26	38
BUCKHORN	1	13	14	33	40	40	50	PAWNEE	4	6	13	16	25	21	31
BUCKHORN	2	26	38	39	55	44	61	PAWNEE	5	5	11	15	24	19	29
BUCKHORN	3	13	17	25	36	28	40	PAWNEE	6	54	73	66	90	73	99
BUCKHORN	5	21	31	26	38	31	44	PAWNEE	7	17	27	25	37	30	43
BUCKHORN	6	1	4	12	20	17	26	PAYNE	2	7	13	20	29	25	36
BUCKHORN	7	15	23	21	31	23	35	PAYNE	3	18	27	26	37	29	42
BUFFER	1	18	26	27	40	29	41	PAYNE	4	2	2	20	26	26	36
BUFFER	2	31	43	42	57	47	64	PAYNE	5	7	9	22	31	27	38
BUFFER	3	21	31	26	38	31	45	PEAR	1	29	39	44	57	51	67
BUNDY	1	90	99	99	99	99	99	PEARCE	1	13	20	25	37	28	40

Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI		Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI	
		Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust			Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust
BUNDY	2	64	82	86	99	98	99	PELONA	1	0	5	10	18	15	24
BURGUNDY	2	20	27	29	40	34	47	PENDLETON	1	59	72	71	89	86	99
BURLESON	2	27	39	35	50	40	56	PENDLETON	2	99	99	99	99	99	99
BURLESON	4	8	10	23	32	28	40	PENINSULA	2	19	28	26	38	29	42
BURNS	1	99	99	99	99	99	99	PENSTOCK	1	98	99	99	99	99	99
BURNS	2	12	20	23	34	27	39	PENSTOCK	10	72	97	98	99	99	99
BURNT MOUNTAIN	1	3	8	13	21	18	28	PENSTOCK	11	30	44	40	56	45	62
BURNT MOUNTAIN	2	5	11	15	24	20	30	PENSTOCK	2	5	9	26	37	34	48
BUTTERFIELD	2	1	5	12	19	17	26	PENSTOCK	3	10	17	31	43	40	55
CABANA	1	17	26	25	37	27	39	PENSTOCK	4	99	99	99	99	99	99
CACHUMA	5	13	19	25	36	26	38	PENSTOCK	5	12	16	30	40	38	51
CACTUS	1	37	52	47	65	52	71	PENSTOCK	6	50	69	76	99	88	99
CADENA	1	20	30	26	38	30	43	PENSTOCK	7	45	60	56	79	73	95
CADENA	2	24	35	30	44	37	53	PENSTOCK	8	45	54	52	65	73	90
CADILLAC	1	99	99	99	99	99	99	PENSTOCK	9	14	21	23	34	26	37
CADILLAC	2	17	26	23	35	25	37	PERIMETER	1	22	27	29	41	37	48
CADWAY	1	58	76	88	99	99	99	PERIMETER	2	2	0	18	20	22	28
CADWAY	2	0	4	12	19	17	26	PERIMETER	3	7	10	23	30	26	36
CAESAR	1	7	12	18	27	23	33	PERIMETER	5	1	0	21	24	29	34
CAESAR	2	8	14	20	30	25	36	PERRIS	1	25	36	30	42	39	54
CAIN RANCH	1	57	77	80	99	92	99	PETIT	1	96	99	99	99	99	99
CAL POLY	2	99	99	99	99	99	99	PETIT	2	22	31	31	44	37	51
CAL POLY	3	37	52	47	64	52	71	PETIT	3	18	28	24	35	27	40
CALAMAR	2	14	22	23	34	24	36	PETIT	4	24	33	32	45	37	51
CALGROVE	2	6	11	17	27	22	33	PETIT	5	82	98	99	99	99	99
CALIBER	1	20	30	25	37	28	41	PHEASANT	1	12	20	21	31	24	36
CALIBER	3	16	24	25	36	29	41	PHEASANT	2	6	12	16	25	20	31
CALIBER	4	15	23	23	34	25	37	PHEASANT	3	27	40	35	51	40	56
CALIBER	6	12	17	24	35	30	43	PICK	2	13	22	24	35	26	38
CALIENTE	4	38	51	52	72	59	79	PICK	3	7	14	18	27	22	34
CALIMESA	1	4	8	15	23	20	30	PICK	4	6	11	16	25	21	31
CALIMESA	2	5	11	16	25	21	31	PICKENS	1	12	19	23	33	28	40
CALLAWAY	2	65	74	93	99	99	99	PICKLE MEADOWS	1	27	34	50	62	55	70
CALSTATE	1	88	99	99	99	99	99	PICKLE MEADOWS	2	11	18	32	45	40	56
CALSTATE	2	12	20	22	33	25	37	PICKLE MEADOWS	3	23	35	33	47	38	54
CAMP NELSON	1	8	13	21	31	25	36	PIEDRA	2	60	73	69	87	86	99
CAMPANULA	1	32	46	42	59	47	65	PINE COVE	1	15	25	28	41	31	44
CAMPANULA	2	27	40	37	52	41	58	PINE COVE	2	3	9	16	26	22	33
CAMPANULA	3	23	35	30	44	34	49	PINE COVE	3	5	11	19	28	24	36
CAMPANULA	4	2	7	12	20	16	25	PINE COVE	4	11	19	24	36	27	40
CAMPANULA	5	64	85	72	96	91	99	PINE COVE	5	13	21	23	34	24	36
CAMPANULA	6	19	29	45	61	57	75	PINE COVE	6	36	51	45	63	49	68
CAMPROCK	1	53	71	62	83	79	99	PINEWOOD	2	27	40	37	52	42	58
CANAL	1	99	99	99	99	99	99	PINTO	1	24	36	32	46	36	51
CANAL	2	53	67	65	86	75	99	PINTO	2	19	29	24	36	26	38
CANAL	3	31	44	42	59	47	65	PINTO	3	0	4	10	17	14	23
CANAL	4	99	99	99	99	99	99	PINTO	4	19	29	25	37	26	38
CANEBRAKE	1	5	2	26	33	33	42	PINWHEEL	1	18	27	25	36	28	41
CANEBRAKE	2	13	13	27	39	35	45	PINZON	1	20	30	28	41	28	41
CANEBRAKE	3	0	3	12	20	17	27	PINZON	2	22	31	27	39	36	49
CANEBRAKE	4	14	18	38	49	48	59	PIONEERTOWN	3	23	34	37	53	43	60
CANEBRAKE	5	21	31	27	39	29	43	PIONEERTOWN	4	7	13	17	27	22	33
CANET	2	5	9	21	30	27	39	PIONEERTOWN	5	8	14	19	29	23	34
CANTINA	1	17	26	26	38	27	40	PLATEAU	1	9	12	23	30	25	36
CANTINA	3	23	35	31	45	37	53	PLATEAU	2	20	28	27	39	31	43
CAPANERO	1	5	11	17	27	23	34	PLATEAU	3	14	18	24	33	27	38
CARANCHO	2	2	7	12	20	17	26	PLATEAU	4	20	30	24	35	30	43
CARANCHO	5	6	11	16	25	20	30	PLATEAU	5	20	27	30	40	35	48
CARANCHO	6	6	12	17	26	21	32	PLATEAU	6	29	41	39	55	44	61
CARATAN	2	59	76	77	99	92	99	PORCELAIN	1	4	9	13	21	18	27
CARBINE	2	9	16	18	28	23	34	PORPHYRY	2	59	67	67	85	84	99
CAREY	2	21	31	27	40	31	44	POSO PARK	1	60	77	85	99	98	99
CARMELITA	2	9	10	35	40	43	50	POTTERY	1	12	18	24	36	27	39
CARMELITA	3	90	99	99	99	99	99	POULTRY	1	99	99	99	99	99	99
CARNEGIE	2	57	71	82	99	95	99	POULTRY	2	20	29	28	40	34	48
CARRIAGE	2	18	28	27	39	28	41	POULTRY	4	7	13	16	25	18	27
CARVER	2	8	14	14	23	16	25	POWELL	2	26	34	36	48	42	57
CARVER	3	6	12	15	23	17	26	POWER	1	28	40	38	52	43	58
CASE	1	27	39	40	55	44	61	PREDATOR	1	17	26	24	36	27	40
CASE	2	19	29	26	38	27	39	PRESTON	1	21	31	27	40	29	42
CASE	3	10	18	19	30	24	36	PRIMROSE	2	12	16	26	35	29	41
CASEY	1	24	36	29	42	33	47	PRIMROSE	3	6	9	20	28	25	36
CASSIDY	1	5	8	19	28	25	36	PRIMROSE	4	3	4	21	29	26	36
CASSIDY	3	88	99	99	99	99	99	PRONGHORN	2	58	75	75	95	87	99
CASSIDY	4	50	64	58	75	75	96	PRONGHORN	3	4	9	14	23	19	29

Circuit	Seg. No	Hi FPI Wind Speed	Hi FPI Wind Gust	Medium FPI Wind Speed	Medium FPI Wind Gust	Low FPI Wind Speed	Low FPI Wind Gust	Circuit	Seg. No	Hi FPI Wind Speed	Hi FPI Wind Gust	Medium FPI Wind Speed	Medium FPI Wind Gust	Low FPI Wind Speed	Low FPI Wind Gust
CASTRO	1	55	71	83	99	96	99	PUESTA	1	15	22	28	41	31	44
CASTRO	3	20	28	29	42	37	48	PUFF	1	1	5	13	20	18	27
CASTRO	4	7	12	18	27	21	32	PUFF	2	3	9	14	23	19	29
CATARACT	2	24	35	32	46	37	52	PURCHASE	1	14	22	24	36	26	39
CATARACT	3	28	39	34	47	40	55	PYLE	1	32	45	43	60	47	65
CEDAR GLEN	1	16	22	27	39	30	42	PYLE	2	27	40	38	53	43	60
CEDAR GLEN	2	4	6	22	31	27	35	PYTHON	1	15	24	25	36	27	40
CEDAR PINES	1	16	23	33	44	40	55	PYTHON	3	10	15	23	32	24	36
CEDAR PINES	2	13	21	24	36	27	40	PYTHON	4	16	25	23	35	25	37
CELLO	1	21	31	28	41	32	45	QUICKSILVER	1	28	37	37	50	42	57
CELLO	2	16	25	25	37	27	40	QUICKSILVER	2	20	29	27	39	30	43
CENTAUR	1	34	48	43	60	47	66	QUICKSILVER	3	61	76	84	99	94	99
CENTAUR	2	35	50	46	64	50	70	QUINBY	1	0	5	11	18	15	24
CHALON	1	29	42	38	54	43	60	QUIXOTE	1	26	38	34	48	38	54
CHAMPION	1	91	99	99	99	99	99	RACER	1	25	36	30	44	33	48
CHAMPION	2	53	69	82	99	94	99	RACER	2	47	64	57	76	63	85
CHARDONNAY	2	13	21	22	33	24	36	RACER	3	22	32	29	42	32	46
CHARIOT	1	35	49	46	63	51	70	RAINBOW	1	37	52	46	64	51	71
CHARIOT	2	18	25	28	41	29	42	RAINBOW	2	9	16	19	28	23	34
CHARIOT	3	99	99	99	99	99	99	RAINBOW	3	15	21	27	39	32	45
CHARLIE	2	35	46	48	63	53	70	RAINBOW	4	10	17	21	32	24	36
CHARLTON	1	99	99	99	99	99	99	RAINBOW	5	22	33	25	37	31	44
CHARLTON	2	21	31	28	41	32	45	RAISIN	2	23	31	38	49	42	57
CHARLTON	3	78	98	99	99	99	99	RAMAC	1	99	99	99	99	99	99
CHATEAU	1	46	62	61	83	77	99	RAMAC	2	45	56	58	74	69	87
CHATTANOOGA	1	5	10	16	25	21	31	RANIER	1	20	30	26	39	28	41
CHATTANOOGA	2	49	67	60	81	66	89	RANIER	3	71	94	93	99	99	99
CHAWA	1	1	4	12	19	16	25	RANKIN	1	9	16	20	30	23	34
CHAWA	2	16	23	29	41	34	49	RANKIN	2	61	76	71	92	88	99
CHAWA	3	11	20	26	38	29	42	RAYBURN	1	4	10	14	23	19	29
CHAWA	4	1	6	18	29	23	35	RAYBURN	2	27	40	31	44	37	52
CHAWA	5	19	29	31	45	37	52	RAYBURN	3	5	11	15	24	20	30
CHAWA	6	42	52	62	75	67	85	RAYBURN	4	1	5	12	20	17	26
CHELLA	2	42	51	56	69	68	84	READY	2	73	94	99	99	99	99
CHEVELLE	2	6	12	18	28	24	35	READY	3	21	31	28	40	31	44
CHEVELLE	3	22	32	28	40	34	48	RED BOX	1	13	20	17	27	20	30
CHEVELLE	4	5	3	24	31	31	38	RED BOX	2	14	22	21	31	24	35
CHINA PEAK	1	83	99	99	99	99	99	RED MOUNTAIN	1	15	23	20	29	22	33
CHINA PEAK	3	49	65	63	83	79	99	RED MOUNTAIN	2	21	31	27	39	32	47
CHUCK WAGON	1	26	38	35	50	39	55	RED MOUNTAIN	3	10	16	13	20	15	22
CHUMASH	1	27	39	36	49	40	55	RED MOUNTAIN	4	12	19	20	30	23	34
CIENIGITAS	3	19	28	28	41	29	42	REDBALL	1	15	24	25	37	27	40
CIRCLE	1	42	59	61	80	72	95	REDINGER	1	99	99	99	99	99	99
CIRCLE	3	75	94	99	99	99	99	REED	1	23	35	26	38	32	46
CISCO	1	99	99	99	99	99	99	REED	2	14	23	24	36	26	39
CISCO	2	38	54	49	68	55	75	REED	3	24	35	27	39	32	46
CLARINET	1	23	33	28	41	35	50	REEDER	2	27	39	35	50	40	56
CLARINET	2	15	23	24	36	27	39	REJADA	1	26	38	38	50	42	58
CLARINET	3	14	23	22	33	24	36	REJADA	2	13	20	24	35	26	39
CLARINET	4	7	12	17	26	22	32	REJADA	3	26	39	36	51	41	57
CLEMSON	1	19	28	27	39	29	42	REJADA	4	75	96	99	99	99	99
CLUB OAKS	2	4	8	15	23	20	29	RESORT	1	21	32	26	38	28	40
COACHELLA	2	76	99	99	99	99	99	RESORT	2	6	11	15	24	19	29
COACHELLA	3	14	23	22	33	23	34	RESORT	3	12	20	21	32	24	36
COBRA	2	17	24	26	38	27	39	RESORT	4	13	21	22	32	24	35
COBRA	3	14	20	26	37	29	42	RESORT	5	63	85	88	99	99	99
COJO	1	19	27	27	39	30	43	RESORT	6	24	36	31	45	37	52
COLLIER	1	17	27	26	38	27	40	REVERSE PEAK	1	12	21	32	47	41	57
COLLIER	2	7	14	18	27	22	33	REVERSE PEAK	2	27	41	49	66	56	77
COLLINS	1	34	46	49	64	54	72	REVERSE PEAK	3	35	52	56	75	62	86
COLT	1	73	97	98	99	99	99	RHODA	1	3	8	13	21	17	27
CONCEPCION	1	15	24	23	34	24	36	RHODA	2	22	32	26	39	33	47
CONCEPCION	2	14	22	19	28	21	32	RICARDO	2	18	26	28	40	30	43
CONCEPCION	3	31	44	41	58	46	64	RICARDO	3	24	35	30	44	34	48
CONCEPCION	4	18	27	26	37	31	44	RIDGE	3	1	1	18	25	24	33
CONCORD	1	9	15	21	31	26	38	RIDGEMOOR	3	28	40	32	46	37	53
CONDOR	1	0	4	11	19	17	26	RIM	3	4	5	22	26	25	31
CONDOR	2	2	5	21	31	26	38	RIM	4	6	8	24	30	29	37
CONDOR	3	14	20	29	40	36	51	RIM	5	3	1	24	27	25	30
CONEJO	1	13	20	23	35	27	39	RIM	6	0	0	20	26	28	35
CONESTOGA	1	13	20	26	37	26	39	RIM	7	64	83	91	99	99	99
CONESTOGA	2	14	22	25	37	28	41	RIMROCK	2	90	99	99	99	99	99
CONFERENCE	1	20	31	26	39	28	41	RITTER	1	17	26	24	36	26	39
CONINE	1	26	39	35	50	40	56	RIVIERA	1	5	10	21	31	27	39
CONINE	2	28	40	36	51	41	57	RMV 1243	1	32	47	43	60	47	66
CONINE	3	36	48	53	70	60	79	ROADRUNNER	1	25	36	30	44	34	49

Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI		Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI	
		Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust			Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust
CONINE	4	33	47	46	64	51	70	ROBIN	1	7	6	21	24	25	32
CONWAY	1	26	37	37	52	42	59	ROBIN	2	20	29	26	37	32	46
CONWAY	2	9	12	27	39	36	50	ROBIN	3	8	15	20	30	24	35
COOLER	2	38	53	47	65	51	71	ROBIN	4	14	22	24	36	26	38
COOLER	3	99	99	99	99	99	99	ROBIN	5	8	14	19	29	24	35
COPPERHEAD	1	30	40	43	55	49	62	ROBINSON CREEK	1	19	26	41	55	48	62
CORINTH	1	16	25	24	36	25	37	ROBINSON CREEK	2	7	14	25	37	30	44
CORINTH	2	11	19	21	32	24	36	ROCKCREEK	1	13	22	27	40	32	47
CORNWALL	1	14	22	26	37	28	41	ROCKHILL	2	10	14	26	37	28	40
CORNWALL	3	36	51	44	62	49	68	ROCKHILL	3	27	39	33	46	38	53
CORONITA	2	23	35	28	41	34	48	ROCKRIDGE	2	19	28	27	39	27	39
CORSAIR	1	23	33	28	40	35	50	ROCKWELL	1	7	11	23	32	26	38
CORSAIR	2	7	9	25	36	29	40	ROI-TAN	1	27	39	35	50	39	56
CORSAIR	3	52	69	69	91	69	91	ROI-TAN	2	99	99	99	99	99	99
CORSAIR	4	4	8	23	34	31	43	ROI-TAN	4	26	38	37	51	41	58
CORSAIR	5	22	29	36	48	40	56	ROI-TAN	5	57	75	83	99	96	99
CORSAIR	6	23	31	48	63	58	75	ROMANUS	2	35	50	44	62	48	67
CORTESE	1	8	13	18	27	23	34	ROMANUS	3	29	41	39	55	43	61
CORTESE	2	1	5	11	18	15	24	ROMANUS	4	12	20	20	30	24	35
COTTONMOUTH	1	39	55	50	68	55	75	ROMANUS	5	3	8	13	21	17	27
COULTER	1	43	56	71	90	83	99	ROMERO	1	20	30	25	37	26	38
COVE	1	23	34	29	42	33	47	ROS	1	24	36	35	49	39	55
COVENTRY	1	12	20	23	35	27	39	ROS	4	7	13	21	31	25	36
COVENTRY	2	22	32	28	40	32	45	ROSA	2	4	9	14	22	19	28
COVENTRY	3	14	21	26	37	28	40	ROSEBUD	1	6	12	18	27	23	34
COVENTRY	4	18	26	26	38	29	42	ROSEBUD	2	45	57	63	82	80	99
COVENTRY	5	15	22	24	36	26	38	ROTEC	2	29	42	36	51	41	58
COVENTRY	6	18	24	36	47	43	58	ROTEC	3	12	20	22	33	24	35
COVEVIEW	2	85	99	99	99	99	99	ROTEC	4	23	35	29	42	33	48
CRAB	1	3	8	15	24	21	31	ROUNDEL	1	61	79	73	95	92	99
CRAB	2	48	67	70	93	80	99	ROUNDEL	3	8	15	18	27	22	34
CRAB	3	11	13	26	33	37	48	ROUNDEL	4	27	39	33	46	39	55
CRAB	4	15	23	26	36	28	41	ROWCO	3	10	14	28	35	34	44
CRABTREE	1	9	16	20	30	24	36	ROXBURY	1	28	41	39	54	45	61
CRAM	2	61	79	86	99	99	99	RUBIN	1	6	9	18	26	22	32
CRAM	3	16	24	20	31	23	35	RUBIN	2	86	99	99	99	99	99
CRAWFORD	1	48	62	73	92	84	99	RUGGLES	2	24	36	30	43	30	44
CRESTLINE	1	5	10	17	26	23	32	RUIZ	1	4	9	16	24	21	31
CRESTLINE	2	2	6	17	26	23	34	RUSTIC	1	40	57	51	70	57	78
CRESTWIND	1	92	99	99	99	99	99	RUSTIC	2	11	18	20	31	23	35
CROFT	1	15	22	28	40	29	42	RUSTIC	3	1	4	13	20	18	27
CROSSON	2	7	11	24	33	28	40	RUSTIC	4	0	3	11	18	16	25
CROWLEY	1	27	40	46	63	53	72	RUSTIC	5	20	29	27	39	30	43
CROWLEY	2	21	32	38	54	45	62	RUSTIC	6	14	22	20	30	24	35
CROWLEY	3	22	31	46	60	49	64	RYE	2	21	31	29	42	34	48
CRUMNER	2	7	11	22	32	27	39	SABRINA	1	46	59	59	79	66	87
CRUMP	1	10	16	22	32	27	38	SABRINA	2	28	40	38	53	44	61
CRUMP	2	10	16	20	30	24	36	SABRINA	3	51	66	63	82	69	90
CRUZ	2	16	22	23	35	28	41	SADDLEBACK	1	22	33	27	40	30	43
CUDDEBACK	2	26	38	34	49	39	55	SADDLEBACK	2	16	24	20	31	22	33
CUSHENBURY	1	14	23	23	34	24	36	SAGE	1	99	99	99	99	99	99
CUSHENBURY	2	15	24	24	36	26	38	SAGEHEN	2	37	41	62	71	65	77
CUTHBERT	1	13	21	24	35	28	40	SAGEHEN	3	33	51	59	83	68	93
CUTHBERT	10	5	10	17	27	23	34	SAGEHEN	4	47	61	68	85	76	95
CUTHBERT	11	28	41	39	55	44	61	SAGINAW	1	18	28	25	37	29	42
CUTHBERT	12	5	9	20	29	25	37	SAINT JO	1	13	19	26	36	28	41
CUTHBERT	2	22	32	29	41	35	50	SAINT JO	2	99	99	99	99	99	99
CUTHBERT	3	7	11	21	31	26	39	SALT CREEK	2	21	29	32	45	38	53
CUTHBERT	4	55	70	80	99	92	99	SALT CREEK	3	2	7	12	19	16	25
CUTHBERT	5	60	75	91	99	99	99	SALT CREEK	4	9	16	19	29	22	33
CUTHBERT	6	17	26	27	39	28	41	SAN NICHOLAS	1	4	6	17	25	23	33
CUTHBERT	7	14	11	26	27	31	38	SAN NICHOLAS	2	47	59	71	89	83	99
CUTHBERT	8	31	45	42	59	47	65	SAN NICHOLAS	3	29	43	39	55	44	61
CUTHBERT	9	43	51	66	80	79	98	SAN NICHOLAS	4	29	41	37	53	42	58
CUYAMA	1	17	24	42	55	49	65	SANCHO	1	9	16	18	28	23	34
CUYAMA	2	1	4	26	36	38	50	SAND CANYON	1	11	18	20	30	23	35
DALBA	1	18	23	31	41	40	53	SAND CANYON	3	24	36	31	45	35	50
DALBA	2	7	10	28	34	31	42	SAND CANYON	4	74	88	99	99	99	99
DALBA	3	13	17	28	36	35	46	SAND CANYON	5	29	42	41	57	46	64
DALBA	4	15	20	29	37	35	46	SAND CANYON	6	1	4	12	19	17	26
DARTMOUTH	1	21	29	27	40	30	42	SAND CANYON	7	3	7	13	21	17	26
DARTMOUTH	2	9	16	18	28	23	34	SAND CANYON	8	15	24	22	33	26	38
DARTMOUTH	3	24	35	26	39	34	48	SANITARIUM	1	99	99	99	99	99	99
DARTMOUTH	4	30	42	40	57	46	63	SAUNDERS	1	36	47	56	72	59	76
DARTMOUTH	5	7	13	18	27	22	33	SAUNDERS	2	40	55	58	79	64	87
DAVENPORT	1	1	3	13	20	19	28	SAUNDERS	3	18	27	28	40	28	41
DAVENPORT	2	1	2	16	24	22	32	SAUNDERS	4	34	49	47	66	53	73

Circuit	Seg. No	Hi FPI Wind Speed	Hi FPI Wind Gust	Medium FPI Wind Speed	Medium FPI Wind Gust	Low FPI Wind Speed	Low FPI Wind Gust	Circuit	Seg. No	Hi FPI Wind Speed	Hi FPI Wind Gust	Medium FPI Wind Speed	Medium FPI Wind Gust	Low FPI Wind Speed	Low FPI Wind Gust
DAVENPORT	3	6	11	18	27	21	32	SAUNDERS	5	9	16	24	35	27	40
DAVENPORT	4	7	12	18	27	23	34	SAUNDERS	6	33	44	54	69	62	80
DAVENPORT	5	4	8	19	29	22	33	SAUNDERS	7	19	29	28	41	34	49
DAVENPORT	6	5	8	19	29	24	35	SAUNDERS	8	9	17	26	38	31	44
DAVENPORT	7	17	25	24	36	28	41	SAUNDERS	9	20	31	27	40	30	43
DEACON	1	99	99	99	99	99	99	SAVORY	1	13	21	22	33	25	37
DEACON	2	10	16	20	30	24	36	SAVORY	2	27	39	38	54	43	60
DEACON	3	22	32	26	38	31	44	SAVORY	3	3	8	12	20	16	26
DEALER	2	5	10	31	41	36	49	SAVORY	4	31	42	40	56	44	61
DEALER	4	99	99	99	99	99	99	SAWPIT	1	53	64	78	96	91	99
DEL CARBON	1	15	20	27	39	34	47	SCALP	1	73	93	99	99	99	99
DEL CARBON	2	10	13	32	39	41	52	SCHMIDT	1	11	17	22	33	25	37
DELUZ	2	6	12	15	24	20	30	SCHMIDT	2	4	7	18	27	24	35
DENTAL	2	9	16	19	29	24	35	SCIURBA	1	89	99	99	99	99	99
DENTAL	3	5	11	15	24	20	30	SCIURBA	2	50	62	63	81	79	99
DEVILS GATE	1	2	4	16	23	22	31	SCIURBA	3	37	46	51	63	58	73
DEVILS GATE	2	68	85	93	99	99	99	SCIURBA	4	0	1	17	25	24	33
DEVINE	2	5	10	18	27	24	35	SDGE 520	1	20	30	25	37	28	41
DEVINE	3	1	5	15	24	21	32	SDGE 521	1	75	99	99	99	99	99
DICE	1	28	39	43	56	47	63	SEACLIFF	1	15	22	25	37	28	41
DICE	2	71	92	99	99	99	99	SEACLIFF	2	22	33	27	39	32	45
DILL	1	15	24	25	36	26	39	SEACLIFF	4	0	2	13	21	19	28
DINELY	1	1	6	11	18	15	25	SEACLIFF	5	0	2	13	20	18	27
DINKEY CREEK	1	15	19	33	41	39	50	SEAFORTH	2	21	31	42	56	48	63
DOBLE	1	23	34	31	45	36	51	SEAWOLF	1	18	27	25	36	26	38
DOBLE	2	21	32	26	38	32	46	SEBASTIAN	2	25	37	29	42	35	49
DOCTORS	2	9	16	19	29	22	34	SEELEY	1	12	16	25	32	28	40
DOCTORS	3	22	32	27	39	31	45	SEELEY	2	21	27	34	42	39	51
DOLORES	1	9	14	22	32	27	38	SEELEY	3	27	37	38	52	45	61
DOLPHIN	1	41	57	51	69	55	76	SERFAS	1	79	99	99	99	99	99
DOMIC	1	7	13	18	28	23	34	SERNA	1	27	39	31	44	36	51
DOMIC	2	36	52	46	64	51	70	SERRA	1	6	8	20	27	24	31
DONLON	2	36	51	47	65	52	71	SERRA	2	2	3	14	18	17	25
DONLON	3	24	35	32	46	37	52	SERRA	3	16	24	25	37	28	40
DONLON	4	24	36	25	37	33	47	SESPE	1	36	51	47	63	51	70
DONNER	1	98	99	99	99	99	99	SEXTON	1	24	35	31	44	34	49
DONNER	2	69	88	99	99	99	99	SEXTON	2	9	16	21	31	26	38
DONNER	3	52	66	66	86	81	99	SEXTON	4	15	23	24	35	25	37
DOROF	1	99	99	99	99	99	99	SEXTON	6	30	41	43	60	49	66
DOROF	2	61	77	93	99	99	99	SEYMOUR	1	6	10	26	35	29	41
DRAGON	2	99	99	99	99	99	99	SHAKE	1	60	77	88	99	99	99
DRAGON	3	99	99	99	99	99	99	SHAKE	2	44	55	70	85	82	99
DRILLER	1	8	11	26	35	29	41	SHASTA	2	0	5	10	18	15	24
DRINKWATER	1	33	47	42	58	47	64	SHEFFIELD	2	7	12	18	27	21	31
DRISKILL	1	20	30	27	39	29	42	SHINE	1	99	99	99	99	99	99
DRISKILL	4	15	24	23	34	27	39	SHINE	2	80	99	99	99	99	99
DRY CANYON	1	26	39	29	42	36	51	SHIPLEY	1	29	43	40	57	45	63
DUKE	1	21	32	26	38	29	42	SHIPLEY	2	11	19	20	30	22	33
DUKE	3	18	28	25	37	27	40	SHIRAZ	1	17	23	27	39	29	42
DWP DRINKWATER	1	86	99	99	99	99	99	SHORELINE	1	84	99	99	99	99	99
DYNAMO	1	26	38	36	51	42	58	SHOVEL	1	3	8	13	21	18	27
DYNAMO	2	10	17	27	39	27	40	SHOVEL	2	8	15	18	27	21	32
DYSART	1	17	26	22	33	25	36	SHOWDOWN	1	18	28	24	36	28	41
DYSART	2	64	86	87	99	99	99	SIAM	2	19	29	28	41	29	42
DYSART	3	8	15	18	27	22	32	SILVA	1	60	74	86	99	98	99
DYSART	4	62	77	69	87	86	99	SIMS	1	23	35	29	42	33	47
EASTER	1	26	38	35	50	40	57	SINALOA	1	13	16	30	41	37	49
EASTER	2	21	32	26	38	27	40	SINKER	1	41	57	51	71	57	78
EASTER	3	14	23	23	34	25	37	SITZMARK	1	60	80	95	99	99	99
EASTER	4	37	52	47	65	52	72	SITZMARK	2	33	44	48	63	54	72
EASTER	5	8	15	18	27	22	33	SITZMARK	3	99	99	99	99	99	99
EBERT	1	99	99	99	99	99	99	SKI	1	13	20	28	41	37	52
EBERT	2	16	25	20	30	23	34	SKINKLE	3	27	39	38	54	42	59
ECHO	1	88	99	99	99	99	99	SKINKLE	5	99	99	99	99	99	99
ECHO	2	19	23	31	43	39	48	SKINKLE	6	9	15	19	29	22	33
EL MIRADOR	3	33	47	42	59	46	65	SKINNER	1	15	24	24	36	25	37
ELAINE	1	26	38	35	50	41	56	SKINNER	2	21	32	26	38	27	40
ELECTRA	1	26	39	36	51	40	57	SKY HI	1	74	96	99	99	99	99
ELSTER	2	8	13	21	31	24	35	SKY HI	3	26	39	34	48	39	55
EMPIRE	1	24	36	30	44	34	48	SKY HI	4	54	71	66	89	75	99
EMPIRE	2	80	99	99	99	99	99	SKYBORNE	2	57	76	72	96	76	99
ENCANTO	2	40	45	55	65	61	70	SKYLAND	1	1	2	20	28	27	36
ENCANTO	3	39	47	55	68	61	75	SKYLAND	2	14	20	28	34	28	40
ENCHANTED	5	1	6	11	18	15	24	SKYLAND	3	15	19	29	40	35	45
ENERGY	1	3	7	13	21	17	27	SLALOM	2	27	39	38	53	43	60
ENERGY	10	24	35	29	42	33	47	SLOPE	1	30	41	49	64	54	71
ENERGY	2	2	6	14	22	19	29	SNO CAT	1	29	41	41	58	46	64
ENERGY	4	18	25	28	41	36	50	SNO CAT	2	29	41	39	55	44	62

Circuit	Seg. No	Hi FPI Wind Speed	Hi FPI Wind Gust	Medium FPI Wind Speed	Medium FPI Wind Gust	Low FPI Wind Speed	Low FPI Wind Gust	Circuit	Seg. No	Hi FPI Wind Speed	Hi FPI Wind Gust	Medium FPI Wind Speed	Medium FPI Wind Gust	Low FPI Wind Speed	Low FPI Wind Gust
ENERGY	5	16	24	27	39	29	42	SNOW VALLEY	3	21	30	30	41	37	50
ENERGY	7	99	99	99	99	99	99	SNOW VALLEY	4	22	29	38	51	47	60
ENERGY	8	22	33	27	40	32	46	SNOW VALLEY	5	30	43	41	56	48	66
ENERGY	9	18	27	28	41	31	44	SNOW VALLEY	6	5	8	22	31	27	36
EQUINOX	1	12	20	21	32	24	35	SNOW VALLEY	7	32	41	40	57	57	76
ERSKINE	1	20	30	26	39	27	39	SNOWCREEK	1	36	50	47	65	52	71
ERSKINE	2	16	24	29	42	32	45	SNOWDRIFT	1	28	41	41	57	46	63
ERSKINE	3	8	13	25	36	28	40	SODA SPRINGS	1	20	26	36	49	43	57
ERSKINE	4	13	21	22	33	26	38	SODA SPRINGS	2	17	26	25	37	29	41
ERSKINE	6	4	8	19	28	24	35	SODA SPRINGS	3	7	13	17	27	22	32
ERSKINE	7	11	20	24	36	28	41	SODA SPRINGS	5	4	9	20	29	23	34
ERSKINE	9	50	66	62	83	68	91	SODA SPRINGS	6	23	32	48	64	56	75
ESCONDIDO	1	40	57	50	68	55	76	SODA SPRINGS	7	21	30	30	43	34	49
ESTABAN	1	11	19	22	33	24	36	SODA SPRINGS	8	27	41	48	67	58	79
ESTABAN	2	25	37	36	51	40	57	SODA SPRINGS	9	29	42	40	56	45	63
ESTABAN	3	6	12	17	26	21	32	SOGGY	2	4	9	14	22	18	28
ESTABAN	4	7	14	18	28	23	34	SONOMA	2	1	5	14	22	20	30
ETHANAC	1	40	56	49	67	54	74	SOPWITH	2	40	55	50	68	55	75
EVERETT	2	85	99	99	99	99	99	SPANADA	1	3	6	17	25	22	32
EVERETT	3	85	99	99	99	99	99	SPANADA	2	5	7	20	28	25	35
EVERETT	4	61	68	89	99	99	99	SPARKS	1	66	73	91	99	99	99
EVERETT	5	25	35	30	42	35	49	SPARLING	1	5	10	15	24	19	29
EVERETT	6	28	40	37	53	42	59	SPICE	1	12	19	23	34	26	38
EVERETT	8	24	32	29	42	37	51	SPIKE	1	27	39	34	48	39	55
EVERETT	9	57	69	81	95	91	99	SPINKS	1	11	16	24	33	28	40
EVITA	1	97	99	99	99	99	99	SPLENDOR	1	33	48	41	58	46	64
EVITA	2	27	38	36	52	42	59	SPLENDOR	2	4	7	19	28	25	36
FACEMASK	2	91	99	99	99	99	99	SPLENDOR	3	54	69	80	99	91	99
FALLS	1	74	96	99	99	99	99	STAGELINE	1	3	7	16	24	20	30
FANO	2	93	99	99	99	99	99	STAGHORN	1	26	39	31	44	38	53
FANO	4	37	48	51	66	57	73	STAGHORN	2	28	41	39	55	44	61
FANO	5	74	95	97	99	99	99	STAGHORN	3	23	34	27	39	30	43
FARMINGTON	1	6	12	17	26	21	32	STANFORD	1	28	41	35	50	40	56
FARMINGTON	2	24	35	35	50	39	55	STANFORD	2	99	99	99	99	99	99
FAYE	1	16	17	25	36	31	43	STANFORD	3	89	99	99	99	99	99
FAYE	2	3	2	25	33	33	43	STANWOOD	4	13	20	24	35	25	37
FAYE	3	24	31	47	58	53	66	STANWOOD	5	2	3	22	29	27	38
FELDSPAR	1	11	16	23	32	27	39	STAR ROCK	1	34	49	43	60	47	66
FELDSPAR	3	54	67	68	87	85	99	STAR ROCK	3	12	19	21	32	25	36
FELDSPAR	4	29	40	41	56	46	63	STAR ROCK	5	10	17	20	30	23	35
FERRARA	3	5	10	16	24	20	30	STARGLOW	2	8	14	17	27	22	33
FERRARA	5	5	11	19	29	22	33	STARGLOW	3	4	9	13	21	18	27
FIELDGATE	1	19	26	27	40	32	44	STARGLOW	4	9	16	19	29	23	34
FIELDGATE	3	13	21	24	36	28	41	STARGLOW	7	13	22	23	35	26	38
FINGAL	2	10	17	19	29	22	33	STATLER	1	5	7	22	31	28	40
FINGAL	4	10	18	20	31	24	35	STATLER	2	8	12	21	31	25	37
FIREBIRD	1	26	38	35	50	41	57	STATLER	3	16	23	26	38	28	41
FIREBIRD	3	30	43	42	57	47	65	STEARNS	1	9	13	25	34	27	39
FIREBIRD	4	5	9	16	25	21	32	STEARNS	2	11	18	24	35	27	40
FIREBIRD	5	20	29	26	37	29	41	STEARNS	3	22	33	25	37	31	44
FLABOB	1	99	99	99	99	99	99	STEEL	1	19	28	25	37	26	38
FLAGSTAFF	1	66	85	91	99	99	99	STEEL	2	7	12	17	26	22	32
FLAGSTAFF	2	42	59	52	71	57	78	STEVENSON	1	26	38	31	44	38	53
FLANDERS	1	7	11	19	28	25	35	STEVENSON	2	24	36	28	41	35	50
FLANDERS	2	7	9	23	32	27	39	STEVENSON	3	2	6	19	28	28	40
FLEETWOOD	2	64	80	92	99	99	99	STONEWOOD	1	51	63	62	78	71	91
FLINTRIDGE	1	57	69	82	99	96	99	STONEWOOD	2	95	99	99	99	99	99
FLINTRIDGE	2	12	13	28	37	34	42	STONEWOOD	3	12	20	24	36	27	40
FLINTRIDGE	3	7	9	24	34	28	39	STONEWOOD	4	30	43	40	56	44	62
FLOODGATE	2	29	42	51	69	57	76	STORES	1	99	99	99	99	99	99
FLOODGATE	3	16	23	32	45	39	54	STORES	2	27	39	34	49	38	54
FLOODGATE	4	16	24	42	56	51	67	STORES	3	16	27	28	40	36	51
FLOODGATE	5	6	11	23	35	30	43	STORES	4	9	17	22	33	25	37
FLOODGATE	6	12	20	38	53	50	68	STORES	5	13	22	24	36	25	37
FLYCATCHER	2	17	21	42	52	50	61	STRATHERN	2	10	17	19	29	22	33
FLYCATCHER	3	25	28	42	51	50	60	STRATHERN	3	12	20	22	33	23	35
FLYING D	1	20	27	37	51	43	58	STRIPER	1	25	37	30	43	35	49
FLYING D	2	41	55	62	79	68	92	STROH	1	22	33	27	40	31	44
FLYING D	3	26	33	46	54	52	65	STROSNIDER	1	16	21	42	54	51	65
FLYING D	4	3	5	20	29	23	33	STROSNIDER	2	32	41	55	70	61	77
FLYING D	5	12	18	28	40	34	48	STUBBY	2	17	26	25	37	26	39
FLYING D	6	18	27	24	36	28	40	STUBBY	3	18	28	25	36	25	37
FLYNN	2	18	26	25	37	27	39	STUBBY	4	12	20	22	33	24	36
FOOTHILL	1	99	99	99	99	99	99	STUTZ	1	14	18	28	40	36	48
FOOTHILL	3	19	29	25	37	28	41	STUTZ	2	7	11	21	31	26	39
FOOTHILL	4	99	99	99	99	99	99	SUBIDA	1	8	15	18	28	23	34
FORTRESS	2	23	35	27	39	32	45	SUBIDA	2	22	33	28	41	30	43
FULLBACK	2	10	17	19	29	24	35	SUCCESS	1	30	32	44	51	51	59
GABBERT	1	3	8	14	22	18	28	SUCCESS	2	14	21	25	37	26	38

Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI		Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI	
		Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust			Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust
GABBERT	2	7	14	16	25	20	30	SUCCESS	3	0	2	15	23	21	31
GABBERT	3	8	14	19	29	23	35	SUCCESS	4	7	14	23	34	25	37
GABBERT	4	99	99	99	99	99	99	SUGARLOAF	1	53	66	74	95	85	99
GABBERT	5	72	85	98	99	99	99	SURREY	1	16	24	26	38	28	41
GABBERT	6	46	49	58	63	63	72	SUSAN	1	99	99	99	99	99	99
GALAHAD	1	17	24	27	39	33	47	SUSAN	2	36	51	48	65	52	71
GALAHAD	2	2	5	18	26	24	34	SUTT	1	28	39	40	54	45	60
GALAHAD	4	17	23	30	42	37	52	SUTT	3	8	11	21	30	25	37
GALAHAD	5	3	5	21	30	27	38	SUTT	4	70	75	96	99	99	99
GALAHAD	6	5	9	21	30	25	37	SUTT	5	15	21	22	33	25	37
GALAHAD	7	15	20	40	51	47	59	SWEETWATER	1	5	10	16	24	20	30
GALAHAD	8	25	33	43	59	49	64	SWEETWATER	2	86	99	99	99	99	99
GALENA	2	23	34	27	40	31	44	TACKLE	1	89	99	99	99	99	99
GALENA	3	99	99	99	99	99	99	TACKLE	2	22	32	27	39	28	41
GAMBLER	4	29	41	45	60	51	70	TAGGERT	1	15	21	28	38	31	44
GAMBLER	5	0	4	24	35	32	44	TAGGERT	3	37	52	48	66	54	74
GARBONI	1	7	14	18	28	22	33	TAHQUITZ	1	16	26	24	36	27	39
GAVIN	2	69	90	99	99	99	99	TAHQUITZ	2	41	58	63	85	69	93
GILMAN	1	20	30	24	35	28	41	TAIWAN	4	11	18	18	27	23	34
GINGER	1	0	3	10	17	15	23	TALLEY	1	10	17	22	33	26	39
GINGER	2	3	8	12	20	16	26	TAMBOURINE	1	23	34	29	42	32	46
GINGER	3	20	29	25	37	28	41	TANAGER	1	3	8	16	25	21	32
GINGER	5	11	18	20	30	21	32	TANAGER	4	18	26	32	45	38	54
GLASSCOCK	2	0	1	20	27	27	38	TANDEM	1	29	42	38	54	44	60
GLOBE MILLS	1	57	69	70	84	86	99	TANDEM	3	23	32	31	43	36	51
GNATCATCHER	1	13	20	26	38	27	40	TAPO	2	17	24	28	40	29	42
GNATCATCHER	3	9	15	23	34	26	38	TAPO	3	19	27	27	40	34	48
GOETZ	1	22	33	27	39	31	44	TAPO	4	12	19	23	34	25	37
GOLDSMITH	2	99	99	99	99	99	99	TAPO	5	7	13	18	27	22	33
GOLDSMITH	4	25	37	29	42	35	50	TAPO	6	19	29	25	37	26	38
GORGE	1	2	2	19	26	26	34	TATANKA	1	56	67	81	99	95	99
GRAHAM	1	48	66	61	82	66	88	TATANKA	2	27	35	32	42	40	55
GRAHAM	2	14	22	22	33	23	35	TATANKA	3	25	30	40	49	48	64
GRANDAD	1	15	23	21	31	23	33	TATANKA	4	16	21	27	37	31	41
GRANDAD	2	14	21	22	32	24	36	TAVA	1	99	99	99	99	99	99
GRANNY SMITH	1	4	10	14	23	19	29	TAVA	2	24	35	30	43	35	49
GRAPEFRUIT	2	27	39	36	51	41	57	TECOLOTE	1	53	65	73	92	88	99
GREAT SALT	1	91	99	99	99	99	99	TECOLOTE	2	1	2	19	27	25	37
GREAT SALT	2	31	45	40	57	45	63	TECOLOTE	3	43	56	55	71	62	81
GREAT SALT	3	62	80	82	99	94	99	TEE VEE	1	27	39	35	50	41	57
GREAT SALT	4	20	31	25	37	26	39	TEJON	1	8	12	21	30	23	34
GRENADE	1	20	30	28	40	29	42	TEJON	3	5	11	15	24	20	30
GROUSE	1	52	68	62	84	77	99	TEJON	6	3	8	14	22	19	28
GRUWELL	2	2	7	13	21	18	27	TEJON	7	9	15	20	29	23	34
GUFFY	1	97	99	99	99	99	99	TEJON	8	3	7	15	23	20	29
GUINNESS	2	88	99	99	99	99	99	TEMPEST	1	14	23	25	36	26	38
GUITAR	1	15	22	23	34	28	40	TENDER	1	25	36	29	42	36	52
GUITAR	2	1	5	12	20	16	25	TENNECO	1	28	35	50	60	56	68
GUITAR	3	13	21	22	32	23	35	TENNECO	10	6	10	32	43	43	58
GUITAR	4	10	17	20	31	23	34	TENNECO	2	33	46	54	72	60	79
GUITAR	5	19	29	25	36	28	41	TENNECO	6	49	65	62	82	79	99
GUITAR	6	14	21	22	33	24	35	TENNECO	9	7	11	33	43	43	54
GUITAR	7	13	21	22	33	24	36	TERMINUS	1	17	26	26	38	26	38
GULL LAKE	1	15	22	40	53	46	61	TERMINUS	2	24	33	34	48	40	55
GUNSITE	1	36	51	47	65	52	72	TERRA COTTA	1	14	22	25	36	27	39
HACKLER	2	23	34	29	42	34	49	TERRA COTTA	2	19	29	25	37	29	42
HAMMERHEAD	1	67	76	93	99	99	99	TEST	2	1	3	14	22	20	30
HAMMOCK	2	30	43	44	61	49	67	TETLEY	1	4	9	20	29	27	37
HAMMOCK	3	4	10	13	21	17	27	TETLEY	3	8	14	24	34	28	40
HANDY	2	46	57	55	68	69	85	TETLEY	4	2	7	16	25	22	33
HARNAGE	4	26	38	38	53	42	59	TETLEY	5	36	50	48	65	55	75
HARNAGE	5	26	38	38	53	43	59	TETLEY	6	66	87	94	99	99	99
HASKELL	2	3	2	26	31	30	39	TEXFI	2	26	38	35	50	40	55
HASKELL	4	76	98	99	99	99	99	TEXFI	3	99	99	99	99	99	99
HASS	1	16	21	27	37	28	40	THACHER	10	7	9	24	34	27	39
HASS	2	1	5	11	19	16	25	THACHER	2	28	41	34	47	39	55
HEAPS PEAK	1	56	70	82	99	96	99	THACHER	3	21	27	34	45	40	53
HEAPS PEAK	2	16	23	27	38	34	45	THACHER	4	15	17	25	34	29	40
HEAPS PEAK	3	7	10	22	30	28	38	THACHER	6	4	4	22	29	27	38
HELENA	1	0	4	12	19	17	26	THACHER	7	23	33	33	45	37	50
HELENKA	1	22	33	27	39	29	42	THACHER	8	10	8	24	32	26	37
HELENKA	2	2	7	12	20	17	26	THORNTON	2	70	90	99	99	99	99
HELENKA	3	1	5	12	20	17	26	TICO	1	4	7	17	25	22	33
HELENKA	4	1	5	13	21	18	27	TICO	4	17	25	26	38	30	42
HELICOPTER	1	26	37	38	52	43	59	TICO	5	5	5	21	26	25	32
HELICOPTER	2	99	99	99	99	99	99	TIMBER CANYON	1	33	46	43	59	48	66
HEMACINTO	2	30	43	39	55	43	61	TIMBER CANYON	2	16	25	23	34	26	38

Circuit	Seg. No	Hi FPI Wind Speed	Hi FPI Wind Gust	Medium FPI Wind Speed	Medium FPI Wind Gust	Low FPI Wind Speed	Low FPI Wind Gust	Circuit	Seg. No	Hi FPI Wind Speed	Hi FPI Wind Gust	Medium FPI Wind Speed	Medium FPI Wind Gust	Low FPI Wind Speed	Low FPI Wind Gust
HENDERSON	2	22	31	29	41	33	47	TIMBER CANYON	3	9	15	18	28	21	32
HERO	1	99	99	99	99	99	99	TIMBER CANYON	4	10	17	17	26	21	32
HERZ	2	14	22	23	34	27	39	TIMCO	1	99	99	99	99	99	99
HI LINE	1	23	34	29	42	34	49	TIN MINE	1	13	21	22	33	23	34
HI LINE	2	14	21	24	35	27	39	TIN MINE	2	58	74	68	87	77	99
HI LINE	3	12	20	17	26	19	29	TIN MINE	3	16	25	20	31	23	34
HIGH SCHOOL	1	37	49	66	85	80	99	TIN MINE	4	2	6	12	20	16	26
HIGH SCHOOL	3	14	21	26	37	29	42	TIOGA	1	14	21	26	38	31	44
HILLARD	1	10	14	23	32	27	39	TIPS	3	14	23	22	33	24	35
HILLARD	2	8	10	25	33	29	41	TITAN	5	13	19	21	31	24	35
HONEYCRISP	2	9	16	18	28	23	34	TOGA	1	11	14	26	36	28	40
HOOK CREEK	1	6	9	26	35	30	41	TOLA	1	75	92	99	99	99	99
HOOLIGAN	1	9	14	21	31	27	39	TOLL	1	25	36	36	51	41	57
HOOLIGAN	2	2	7	13	21	18	27	TOLL	2	39	54	51	70	56	77
HORIZON	1	13	17	24	34	26	38	TOMAHAWK	1	2	7	12	20	17	26
HORIZON	2	6	6	18	25	23	33	TOMAHAWK	2	6	12	16	25	21	31
HORNTOAD	2	36	46	45	58	56	72	TOMAHAWK	3	99	99	99	99	99	99
HORNTOAD	3	11	15	27	36	27	39	TONNER	1	55	68	80	99	92	99
HORNTOAD	4	16	22	28	39	34	46	TONNER	2	19	26	30	43	34	47
HORNTOAD	5	21	29	29	41	33	45	TONTO	2	18	28	24	35	26	38
HORSE MOUNTAIN	1	37	53	45	64	50	69	TORONTO	3	20	29	38	51	43	58
HORTON	1	95	99	99	99	99	99	TOWNHALL	2	56	73	69	89	78	99
HOSPAT	3	27	38	31	44	38	53	TOWNHALL	3	16	25	24	36	25	37
HOSPAT	4	24	36	32	46	36	51	TOWNHALL	4	21	31	27	39	28	40
HOSS	2	17	26	29	42	33	47	TOWNHALL	5	24	36	33	47	38	53
HOT SPRINGS	2	1	3	13	20	18	27	TRAM	2	27	39	36	50	40	57
HOT SPRINGS	3	10	15	24	35	27	39	TRAUTWEIN	2	13	21	23	35	25	36
HOVATTER	1	2	6	15	24	21	31	TRAUTWEIN	3	8	15	19	30	22	33
HUBBLE	2	72	85	96	99	99	99	TREMAINE	1	4	8	15	24	21	31
HUCKLEBERRY	1	13	21	24	36	28	41	TREMAINE	2	15	19	31	41	36	46
HUCKLEBERRY	2	5	11	16	25	21	31	TREMAINE	3	14	21	27	36	28	41
HUCKLEBERRY	4	0	4	10	17	14	23	TREVINO	1	28	41	41	57	45	63
HUGHES LAKE	1	11	18	21	31	24	35	TRIUNFO	1	55	69	85	99	99	99
HUGHES LAKE	2	20	30	25	37	29	42	TRIUNFO	2	9	15	20	30	24	35
HUGHES LAKE	5	16	25	22	33	25	37	TROUT	1	65	87	94	99	99	99
HURLEY	1	19	28	35	49	41	57	TROUT	2	47	62	54	71	72	94
HURLEY	2	24	33	46	59	52	67	TROUT	3	48	63	65	86	79	99
HURST	1	21	31	27	39	32	46	TRUMBLE	1	14	23	22	33	25	37
HURST	3	24	34	29	43	36	51	TRUMP	1	0	0	16	25	22	32
HURST	4	3	8	16	25	22	33	TRUMPET	2	6	12	15	24	19	29
ICE HOUSE	1	29	42	42	57	46	64	TRUMPET	3	0	4	11	18	16	25
IDA	1	99	99	99	99	99	99	TUBA	1	20	29	27	39	31	44
IDA	2	13	21	23	35	26	38	TUBA	2	21	32	27	40	31	45
IDA	3	13	21	23	35	26	38	TUBA	3	21	31	29	42	32	46
IDA	4	5	10	18	27	23	34	TUDOR	1	13	21	24	35	26	38
INDEPENDENCE	1	50	62	63	80	79	99	TUDOR	2	10	17	21	32	23	35
INDEPENDENCE	2	62	76	90	99	99	99	TUFA	1	11	19	30	43	39	54
INSPIRATION	1	99	99	99	99	99	99	TUFA	2	2	7	13	21	18	27
INTAKE	2	10	12	30	39	38	51	TULLY	1	28	36	41	52	46	58
INTAKE	3	16	23	27	40	30	43	TULLY	2	16	22	29	41	30	43
INTERIOR	1	28	41	36	51	40	57	TUNA	3	63	82	91	99	99	99
INTERIOR	2	80	99	99	99	99	99	TUNA	4	30	43	40	56	45	63
INTERIOR	3	13	20	20	30	22	33	TUNA	5	64	82	92	99	99	99
INTERIOR	4	34	48	45	62	50	68	TUNA	6	91	99	99	99	99	99
INTERIOR	5	24	35	34	49	39	55	TUNGSTEN	1	68	93	98	99	99	99
INTERIOR	6	19	29	22	34	27	39	TUNNEL	2	82	99	99	99	99	99
INTERIOR	7	27	40	34	49	38	54	TURNPIKE	3	99	99	99	99	99	99
INTERIOR	9	99	99	99	99	99	99	TURNPIKE	4	21	32	27	40	30	43
INTERN	3	17	26	24	35	24	35	TWIN LAKES	1	15	17	28	38	29	41
INTERN	4	30	43	40	56	44	62	TWIN LAKES	2	65	84	95	99	99	99
INTERPACE	2	30	43	40	57	45	63	TWIN LAKES	3	88	99	99	99	99	99
INTERPACE	3	23	35	33	47	37	52	TWIN LAKES	6	37	47	52	66	58	75
INTERPACE	4	14	23	22	33	22	33	TWIN LAKES	7	22	32	29	41	32	45
INVADER	2	15	24	23	35	25	37	TWIN LAKES	8	47	61	57	73	67	87
INYO LUMBER	1	17	27	27	39	27	40	TWIN PEAKS	1	8	10	22	27	30	39
INYO LUMBER	2	99	99	99	99	99	99	TWIN PEAKS	2	16	22	27	36	29	40
INYO LUMBER	3	62	81	78	99	95	99	TWIN PEAKS	3	28	37	36	49	40	55
IRAN	1	27	39	40	56	44	62	TWISTER	2	26	39	31	44	38	52
IRAN	2	21	31	27	39	30	43	UNDERWOOD	1	53	73	67	90	74	99
IRAN	3	40	56	53	69	57	77	UNDERWOOD	4	50	69	68	90	72	97
IRON	1	65	86	99	99	99	99	UNDERWOOD	5	46	64	64	85	70	93
IRVINGTON	2	56	64	80	96	92	99	UNDERWOOD	6	32	46	58	78	63	85
JADE	2	23	34	28	41	33	48	UNIVERSITY	1	99	99	99	99	99	99
JAKE	1	6	12	18	28	23	34	URBITA	2	2	6	13	21	18	28
JARVIS	2	10	16	16	24	18	27	URBITA	3	85	99	99	99	99	99
JARVIS	3	47	63	76	99	89	99	URBITA	4	26	38	34	49	38	54
JARVIS	4	9	16	17	26	19	29	UTE	1	25	37	29	42	35	49

Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI		Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI	
		Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust			Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust
JARVIS	5	18	27	30	43	34	49	VAL VERDE	1	9	16	20	30	24	35
JASPER	2	29	42	37	52	41	57	VALLECITO	1	26	39	33	48	37	53
JELLYSTONE	4	5	11	15	23	19	29	VALLECITO	4	4	7	17	25	22	32
JELLYSTONE	5	6	13	16	25	20	31	VALMONTE	1	32	39	51	63	56	69
JENKS LAKE	1	22	33	30	44	36	51	VANDERLIP	1	99	99	99	99	99	99
JENKS LAKE	2	15	23	26	38	30	43	VARGAS	2	44	53	57	72	75	94
JERRY	1	15	23	20	30	24	35	VARGAS	3	61	79	88	99	99	99
JERRY	2	28	41	39	54	44	62	VARGAS	4	74	85	99	99	99	99
JERUSALEM	1	91	99	99	99	99	99	VASQUEZ	2	79	99	99	99	99	99
JERUSALEM	2	68	86	82	99	93	99	VENGEANCE	2	39	54	48	66	53	73
JOB	1	1	5	21	31	27	40	VENGEANCE	3	51	57	75	87	87	99
JORDAN	1	8	12	23	33	26	38	VENUS	1	83	99	99	99	99	99
JORDAN	10	1	5	18	27	23	33	VENWIND 1	1	99	99	99	99	99	99
JORDAN	11	31	39	51	65	57	72	VENWIND 4	1	27	39	40	56	45	63
JORDAN	12	13	19	22	31	24	35	VERA CRUZ	1	12	20	20	31	24	36
JORDAN	13	32	46	48	65	53	72	VERA CRUZ	2	13	20	23	34	25	37
JORDAN	2	47	60	59	76	65	85	VERA CRUZ	4	9	15	18	28	22	33
JORDAN	3	14	22	23	35	27	39	VERA CRUZ	5	30	38	41	53	47	61
JORDAN	4	13	20	23	34	28	40	VERDEMONT	1	23	34	31	44	34	48
JORDAN	5	22	32	30	43	34	48	VERDEMONT	2	54	68	79	99	93	99
JORDAN	6	21	27	45	57	55	69	VERDEMONT	3	86	99	99	99	99	99
JORDAN	7	15	18	40	50	50	62	VERDEMONT	4	95	99	99	99	99	99
JORDAN	8	17	23	43	55	54	67	VERDEMONT	5	11	19	22	33	25	37
JORDAN	9	10	15	24	34	27	39	VERDEMONT	6	20	31	25	37	27	40
JUBILEE	1	31	44	42	59	48	66	VERDUGO	1	6	6	27	33	30	41
JUDSON	1	36	51	45	62	49	68	VERDUGO	2	21	31	29	42	29	42
JUDSON	2	37	53	49	67	54	74	VERDUGO	3	22	32	32	45	38	53
JUPITER	1	89	99	99	99	99	99	VERDUGO	4	20	31	31	44	36	51
KEENE	1	12	19	23	34	26	38	VETERANS	2	15	22	24	35	25	36
KEENE	3	4	10	15	23	20	30	VETERANS	4	36	49	45	62	51	70
KELLER	1	8	15	17	27	22	33	VICASA	3	6	12	17	26	20	30
KENO	1	0	4	21	31	25	37	VICASA	4	1	2	14	21	19	28
KENO	2	9	15	35	48	44	59	VICASA	5	2	2	21	29	27	34
KENO	3	47	64	59	79	65	89	VICASA	6	6	7	21	29	25	31
KENO	5	10	17	30	44	38	54	VICASA	7	24	29	36	46	41	54
KERRY	1	9	15	21	32	26	38	VIDEO	1	41	51	62	77	74	93
KICKAPOO TRAIL	1	5	11	16	25	20	31	VIDEO	3	39	54	50	69	55	75
KILKENNY	1	37	53	49	65	53	72	VIENTO	1	11	19	22	33	25	37
KILKENNY	2	13	17	28	40	33	45	VIOLET	1	9	13	24	34	28	40
KILTS	1	13	20	22	33	25	37	VULCAN	1	33	47	43	59	46	63
KILTS	2	67	89	90	99	99	99	WAHOO	2	5	9	19	28	24	35
KINGSFORD	2	19	28	25	38	26	38	WAITE	2	22	32	30	42	34	48
KINNELOA	1	28	30	41	50	48	60	WAITE	3	16	25	23	34	25	37
KINNELOA	3	9	14	22	31	26	37	WARHAWK	2	7	13	17	26	21	32
KINSEY	1	15	24	25	37	26	39	WARHAWK	3	35	50	44	62	49	67
KINSEY	2	3	6	15	23	19	29	WEESHA	1	26	38	31	45	36	51
KINSEY	4	24	36	32	46	36	51	WEESHA	2	28	41	40	56	45	62
KINSEY	5	22	32	29	42	34	48	WEESHA	3	18	28	25	37	27	39
KINSMAN	1	99	99	99	99	99	99	WELCH	1	39	55	47	66	52	72
KIRBY	1	99	99	99	99	99	99	WELCH	2	12	19	19	29	22	33
KIRBY	2	42	58	53	73	59	80	WELCH	3	24	35	36	51	41	57
KLEVEN	1	24	35	27	40	33	47	WESTBLUFF	1	1	6	10	17	14	23
KLEVEN	2	23	32	27	40	34	48	WESTBROOK	1	9	16	19	29	24	35
KONA	2	99	99	99	99	99	99	WESTFALL	1	12	17	27	40	31	43
KRUEGER	2	99	99	99	99	99	99	WHIP	2	25	36	34	49	39	55
KUEHNER	1	24	24	45	45	48	55	WHIPSTOCK	1	4	8	18	26	23	34
KUEHNER	2	3	5	16	24	22	32	WHIPSTOCK	2	32	43	41	58	47	64
KUEHNER	3	12	20	22	33	26	38	WHIPSTOCK	3	28	41	40	55	45	62
KUFFEL	1	2	4	25	33	29	37	WHIPSTOCK	4	17	22	28	40	33	46
KULBERG	1	51	65	61	78	71	92	WHIPSTOCK	5	9	15	23	33	27	39
KWIS	2	26	36	31	43	38	52	WHIPSTOCK	6	15	22	27	39	30	43
LA GRANDE	1	24	34	27	39	34	49	WHISPER	2	66	85	92	99	99	99
LA MANCHA	1	7	13	18	27	23	34	WHITECLIFF	1	18	26	27	40	29	43
LA MANCHA	2	17	25	26	39	28	40	WHITECLIFF	3	21	32	27	40	29	42
LA MANCHA	3	11	18	21	31	24	36	WHITECLIFF	4	12	19	26	37	28	40
LA MANCHA	4	2	4	16	23	21	31	WHITEHORN	2	20	30	25	37	28	41
LA SIERRA	1	5	11	15	23	19	29	WHIZZIN	1	9	15	20	30	23	35
LA SIERRA	2	99	99	99	99	99	99	WIGWAG	1	16	25	26	38	27	40
LACRESTA	1	4	9	14	22	18	28	WILDOMAR	1	17	26	26	38	26	39
LACRESTA	2	21	32	25	37	30	43	WILDOMAR	2	7	13	16	25	20	30
LADERA	1	99	99	99	99	99	99	WILDOMAR	3	9	15	17	27	21	32
LAKELAND	1	7	11	22	32	27	38	WILDOMAR	4	4	9	13	21	17	27
LAKELAND	2	5	10	17	26	21	32	WILSON CREEK	1	11	16	24	35	27	39
LAMANDA	1	49	61	75	95	87	99	WINERY	2	3	9	13	21	17	27
LAMBDA	2	32	43	43	59	49	64	WINERY	4	18	28	24	36	27	40
LANDERS	1	28	40	40	57	44	62	WOBEGONE	2	5	10	14	23	19	29
LANE	1	21	29	30	39	34	46	WOBEGONE	3	13	21	23	34	26	39
LANE	2	11	8	32	34	37	42	WOBEGONE	4	3	9	13	21	18	27

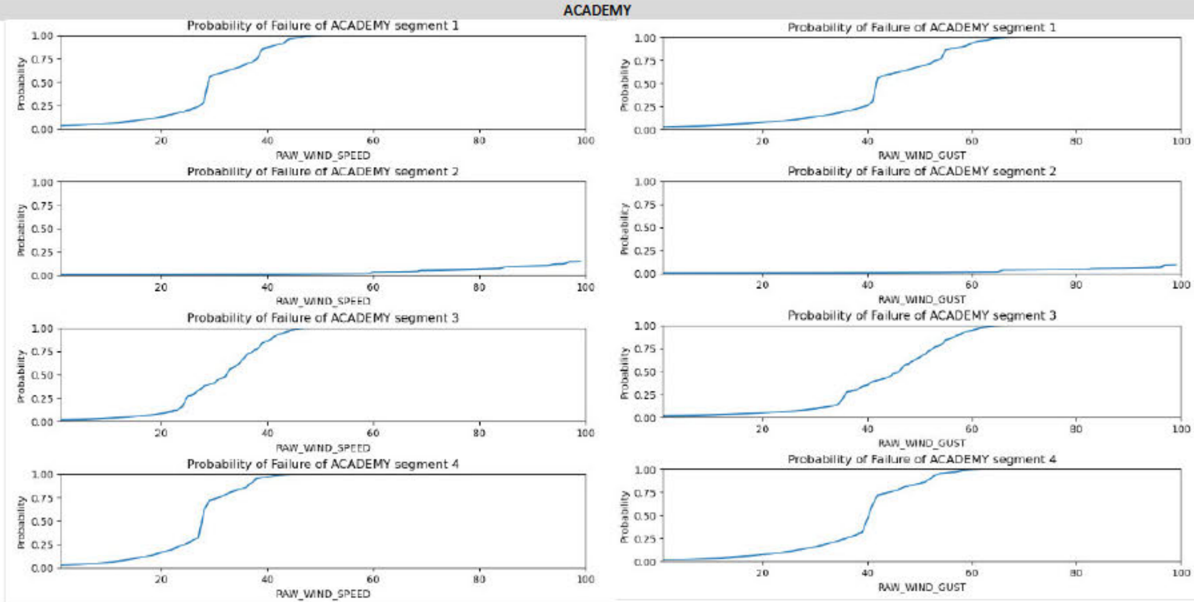
Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI		Circuit	Seg. No	Hi FPI		Medium FPI		Low FPI	
		Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust			Wind Speed	Wind Gust	Wind Speed	Wind Gust	Wind Speed	Wind Gust
LANGER	1	10	17	21	31	25	37	WOBEGONE	6	0	4	10	17	14	23
LANGER	2	16	23	27	40	30	42	WOBEGONE	7	15	23	22	33	25	37
LARCH	2	32	46	44	61	49	67	WRIGLEY	1	23	35	29	43	34	48
LARCH	3	99	99	99	99	99	99	WYLE	1	18	28	27	39	27	40
LARK	1	17	24	27	39	31	42	WYLE	2	52	66	78	99	93	99
LARK	2	5	7	20	26	25	35	YANKEE	1	99	99	99	99	99	99
LASKER	1	4	9	15	24	20	31	YOSEMITE	1	15	21	28	39	35	50
LAST	1	35	50	44	62	48	67	YUCATAN	1	41	48	56	68	71	87
LAUDA	1	21	32	25	37	27	39	YUCATAN	2	24	35	28	40	34	49
LAUDA	2	18	28	25	37	25	37	ZENDA	1	26	37	36	50	40	56
LAUDA	3	25	37	33	47	36	51	ZENDA	2	13	19	22	32	25	36
LAUDA	4	99	99	99	99	99	99	ZENDA	3	17	23	36	48	43	59
LAWMAN	1	19	28	27	39	29	42	ZENDA	4	10	16	23	34	28	40
LAWMAN	2	16	22	28	41	30	43	ZEVO	2	99	99	99	99	99	99
LAWMAN	3	8	8	34	41	42	52	ZONE	2	10	17	19	29	23	35
LAZARO	1	18	28	24	36	26	38	ZONE	3	0	4	11	19	16	25
LEMONADE	2	0	2	19	26	24	35	ZONE	4	5	9	16	24	21	31
LEON	2	14	22	24	36	27	40	ZONE	5	12	19	24	35	27	39
LESSER	1	13	21	26	38	28	41	ZONE	6	5	11	16	24	20	30
LESTER	1	99	99	99	99	99	99	ZONE	7	1	4	12	19	17	26

PROBABILITY OF FAILURE CURVES

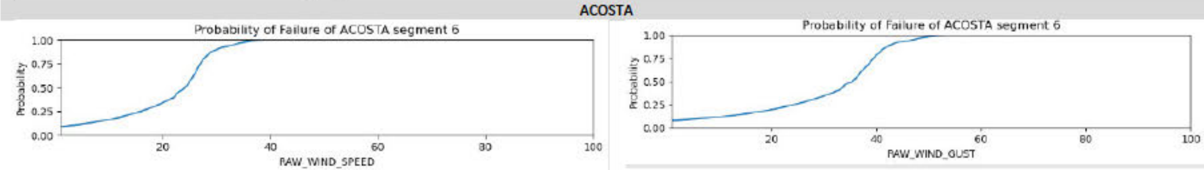
Table A.4: Wind Speed and Wind Gust Probability of Failure Curves.

For segments activated during the October 26, 2023 to November 2, 2023 big event.

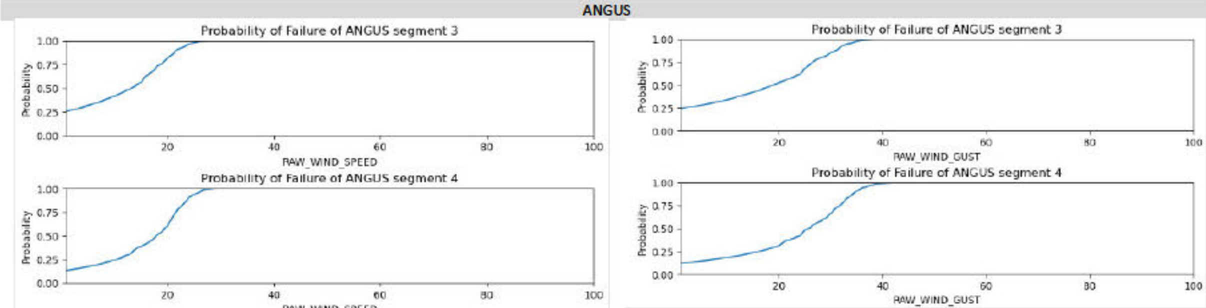
ACADEMY



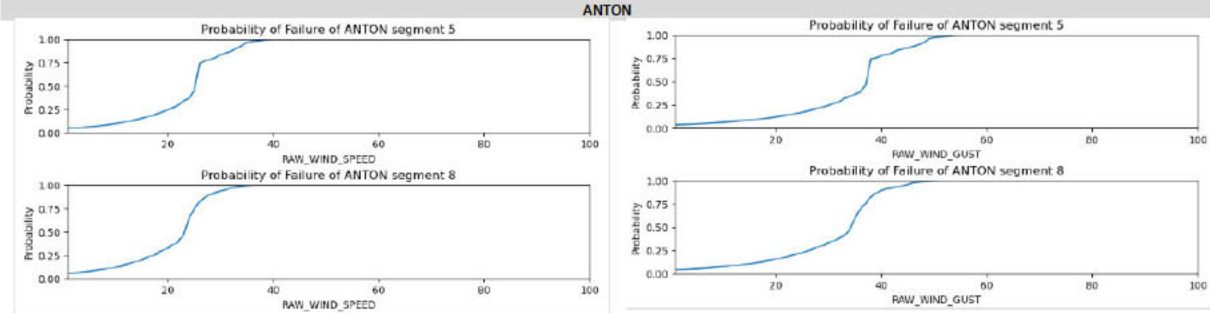
ACOSTA



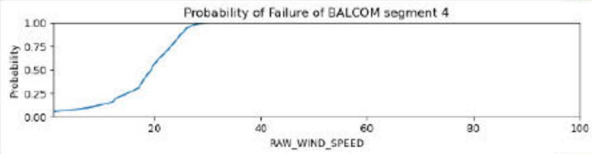
ANGUS

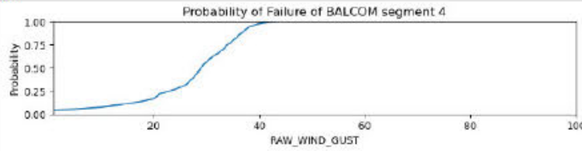


ANTON



BALCOM





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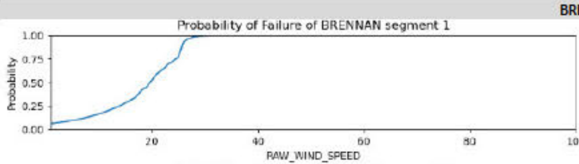

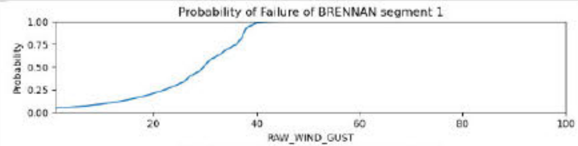

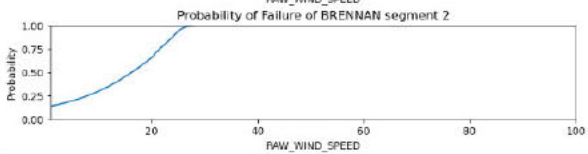

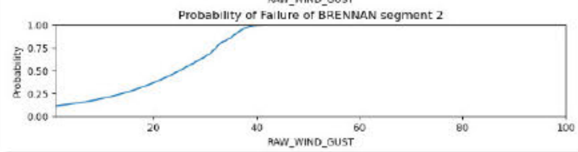

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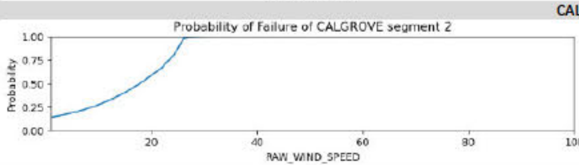
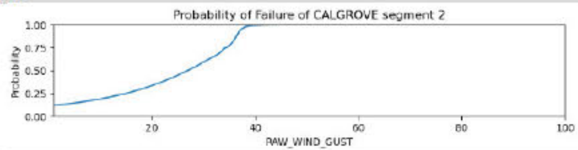
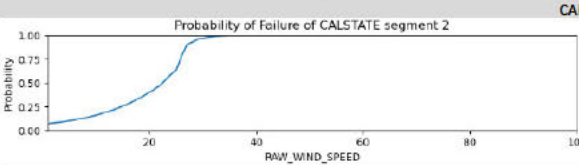
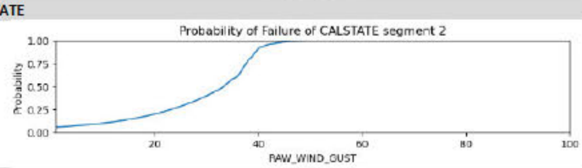


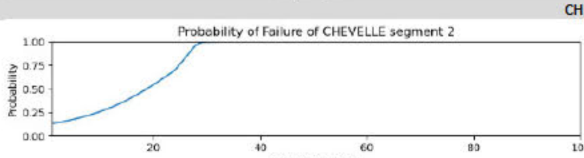


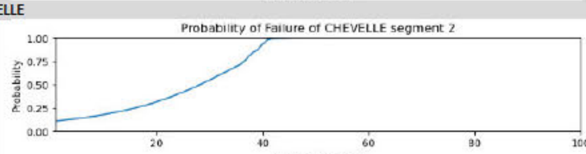
CALSTATE

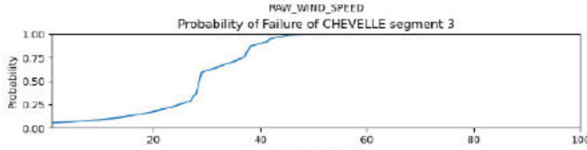


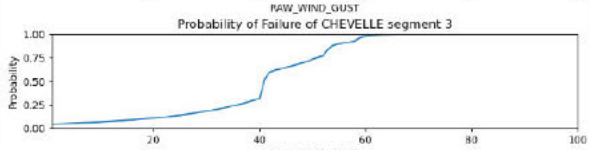


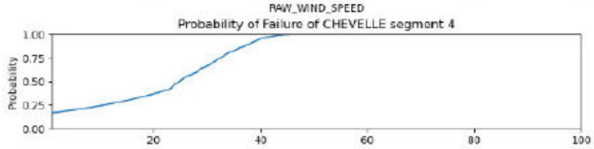
CHEVELLE

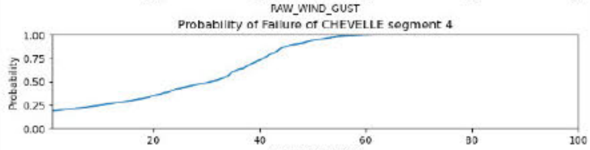




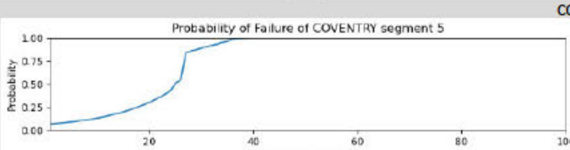


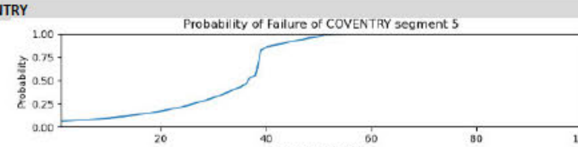


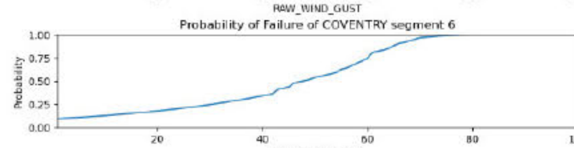




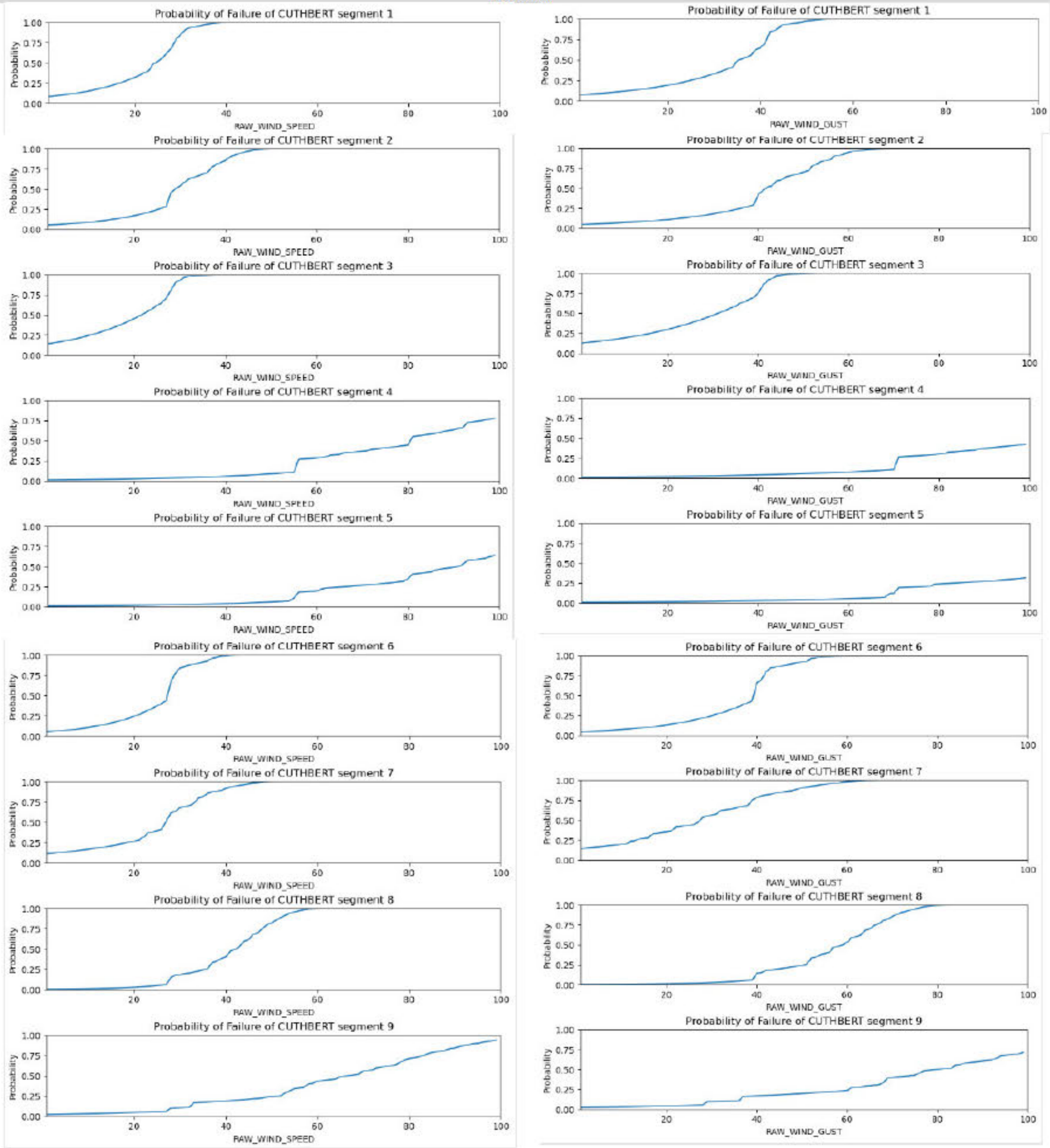
COVENTRY





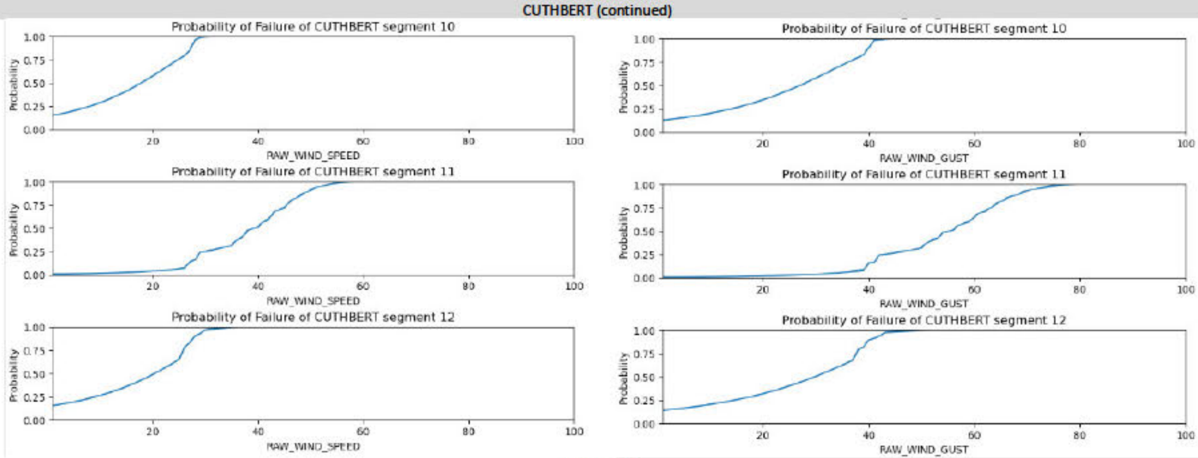


CUTHBERT

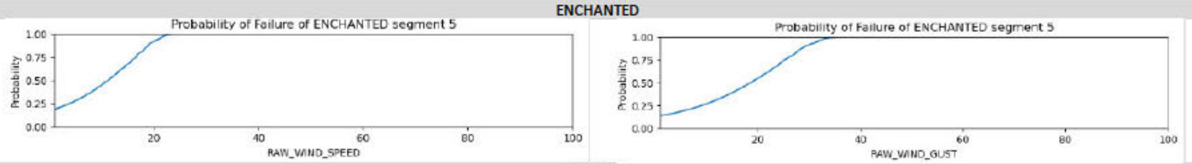


Probability of Failure of CUTHBERT segment 1
Probability
RAW_WIND_SPEED
Probability of Failure of CUTHBERT segment 1
Probability
RAW_WIND_GUST
Probability of Failure of CUTHBERT segment 2
Probability
RAW_WIND_SPEED
Probability of Failure of CUTHBERT segment 2
Probability
RAW_WIND_GUST
Probability of Failure of CUTHBERT segment 3
Probability
RAW_WIND_SPEED
Probability of Failure of CUTHBERT segment 3
Probability
RAW_WIND_GUST
Probability of Failure of CUTHBERT segment 4
Probability
RAW_WIND_SPEED
Probability of Failure of CUTHBERT segment 4
Probability
RAW_WIND_GUST
Probability of Failure of CUTHBERT segment 5
Probability
RAW_WIND_SPEED
Probability of Failure of CUTHBERT segment 5
Probability
RAW_WIND_GUST
Probability of Failure of CUTHBERT segment 6
Probability
RAW_WIND_SPEED
Probability of Failure of CUTHBERT segment 6
Probability
RAW_WIND_GUST
Probability of Failure of CUTHBERT segment 7
Probability
RAW_WIND_SPEED
Probability of Failure of CUTHBERT segment 7
Probability
RAW_WIND_GUST
Probability of Failure of CUTHBERT segment 8
Probability
RAW_WIND_SPEED
Probability of Failure of CUTHBERT segment 8
Probability
RAW_WIND_GUST
Probability of Failure of CUTHBERT segment 9
Probability
RAW_WIND_SPEED
Probability of Failure of CUTHBERT segment 9
Probability
RAW_WIND_GUST

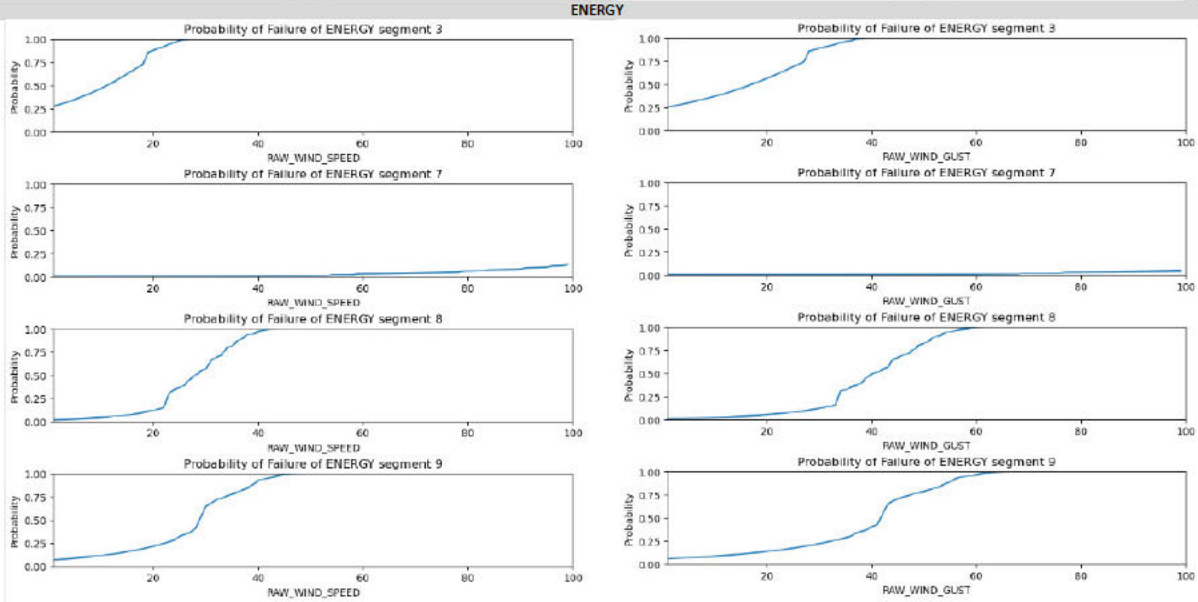
CUTHBERT (continued)



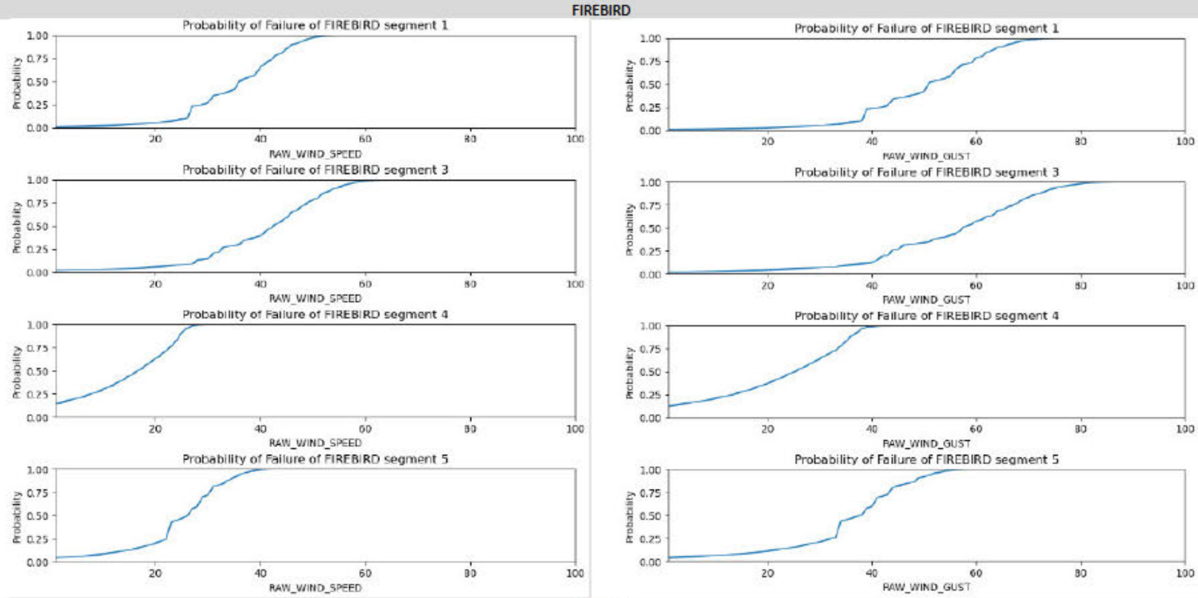
ENCHANTED



ENERGY



FIREBIRD



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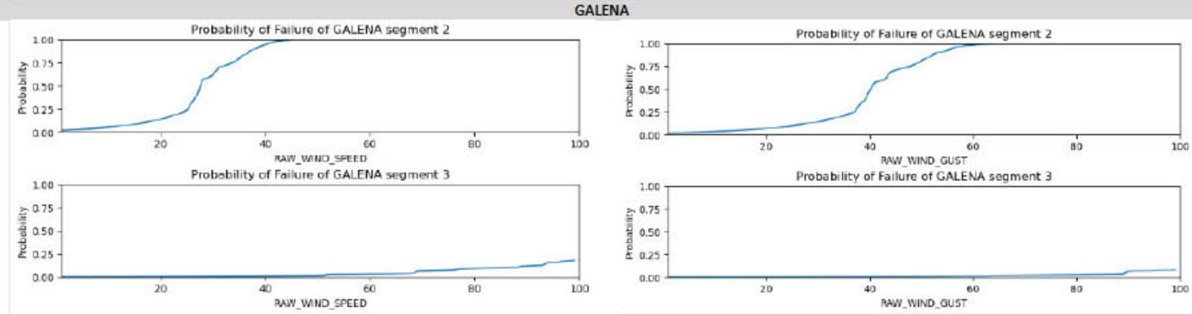
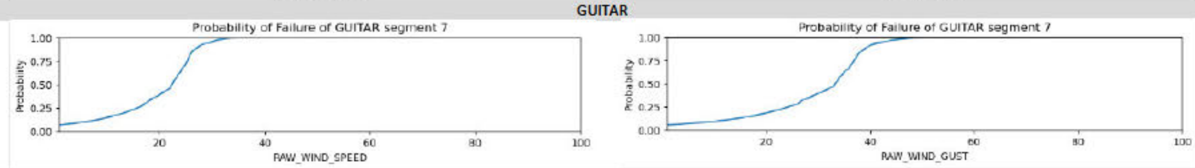
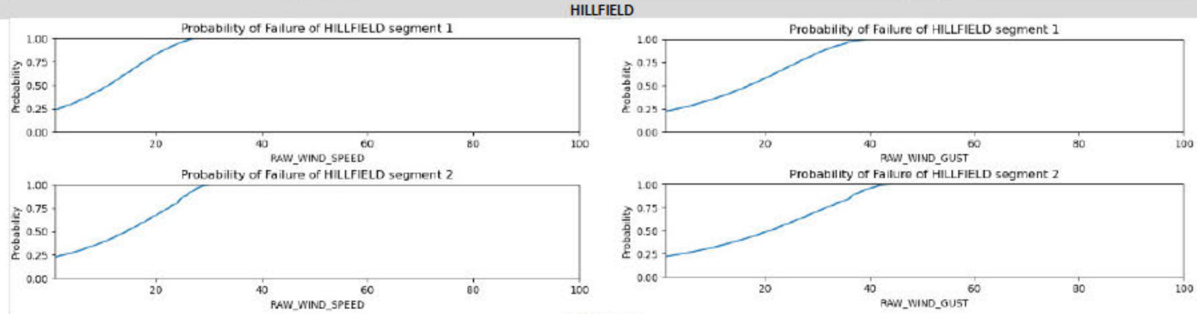


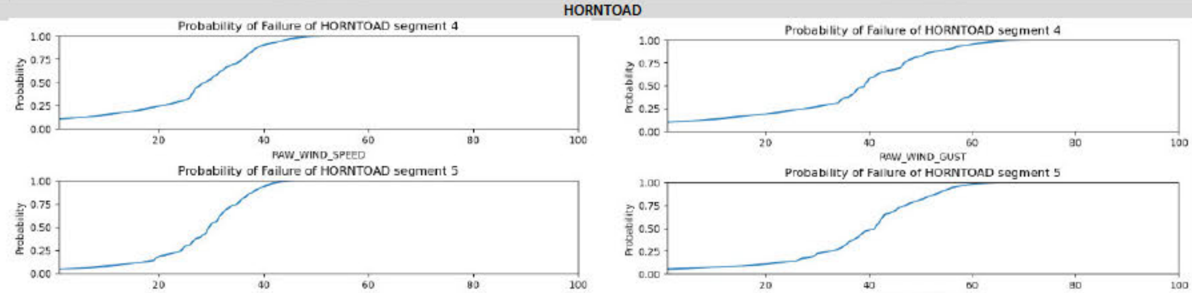
GUITAR



HILLFIELD



HORNTOAD



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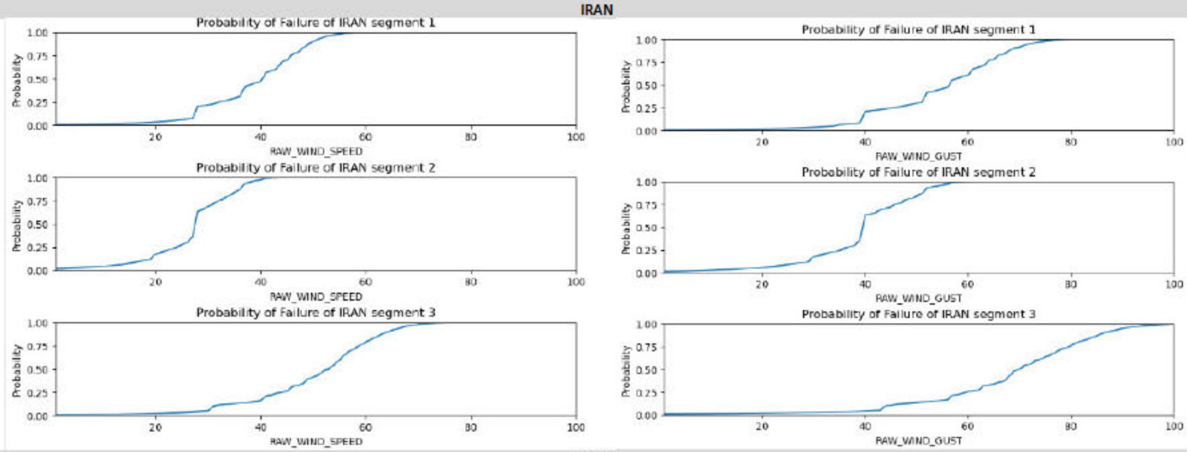
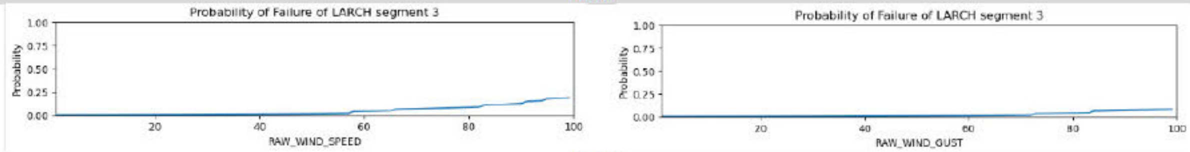
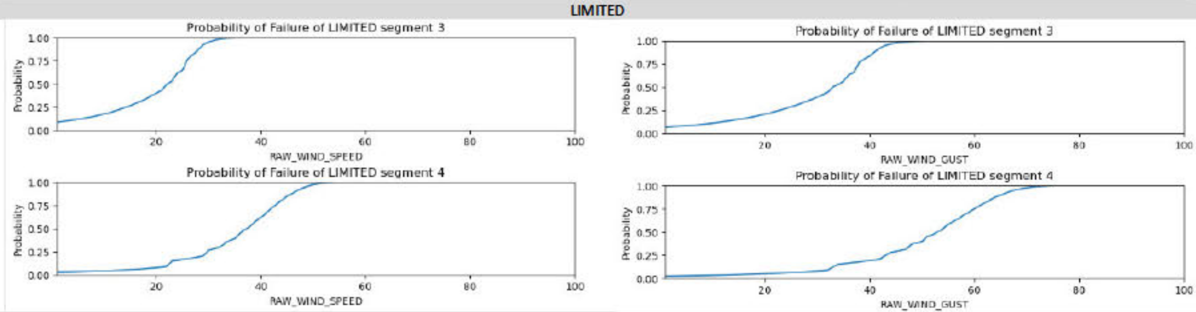


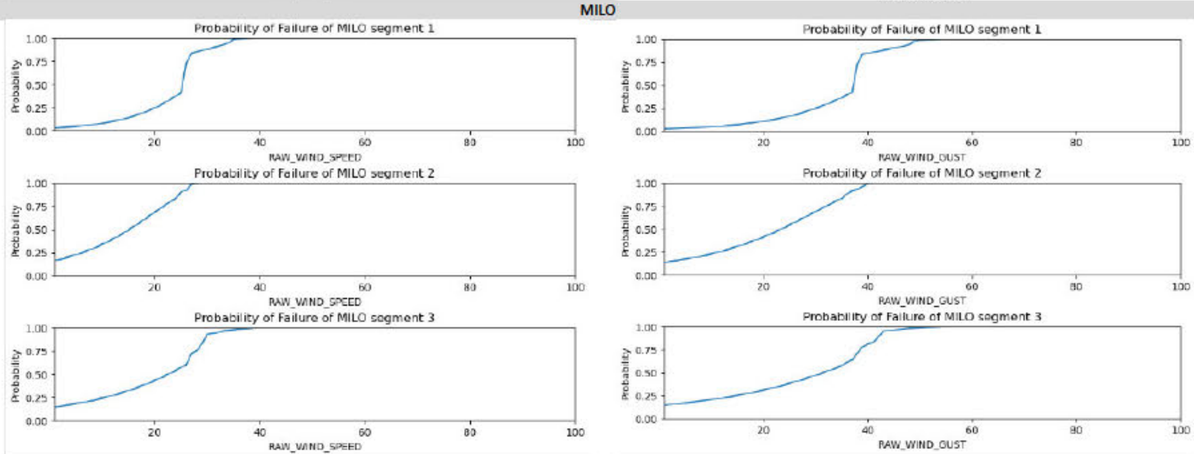
LARCH



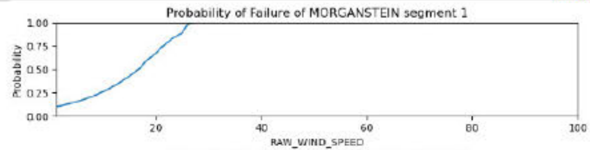
LIMITED

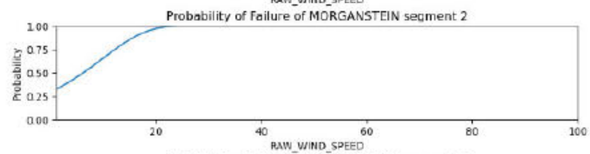


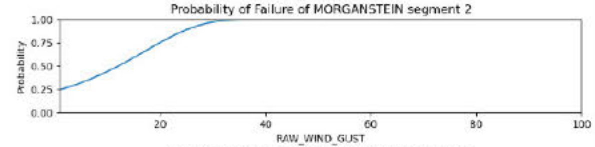
MILO



MORGANSTEIN







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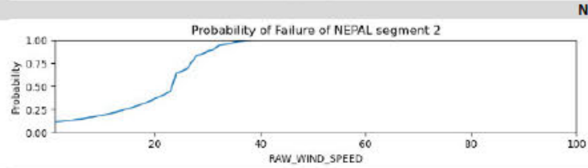
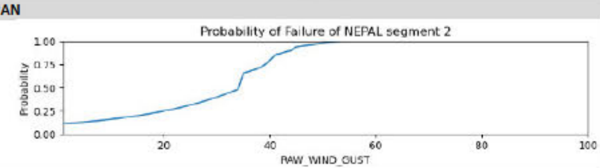
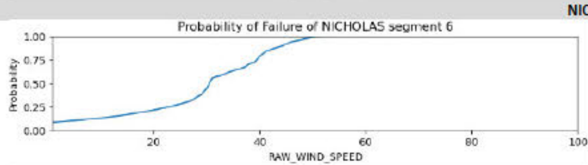
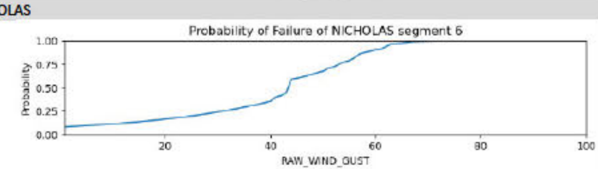


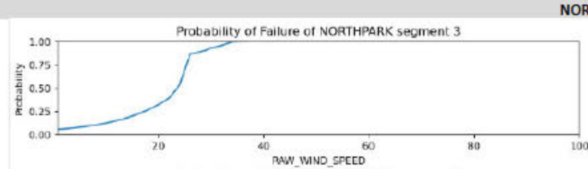


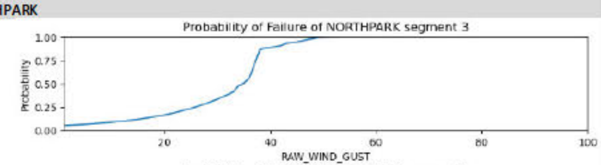
NICHOLAS

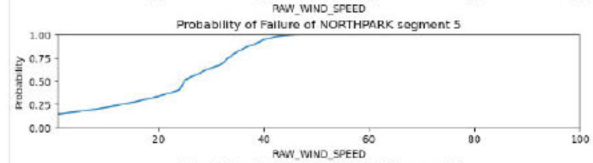


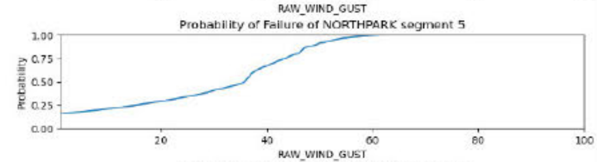


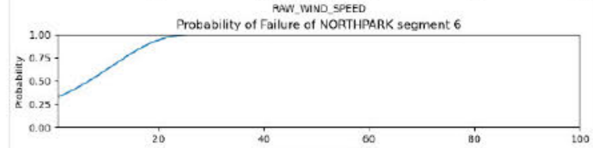
NORTHPARK

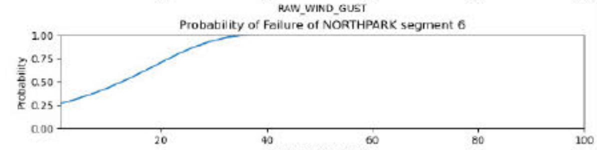


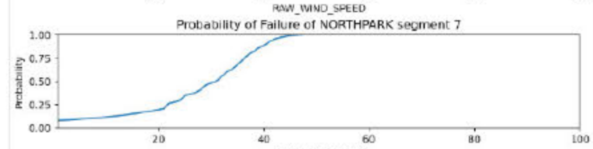


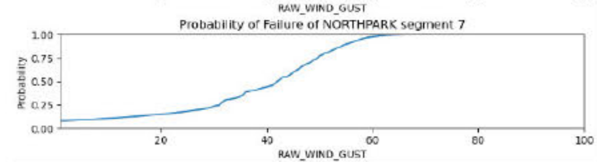




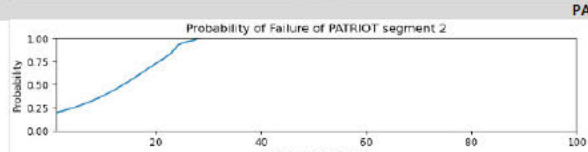


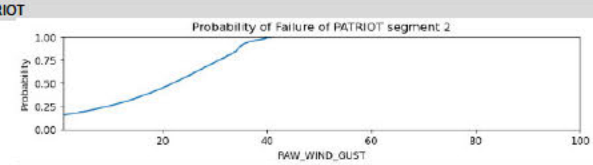




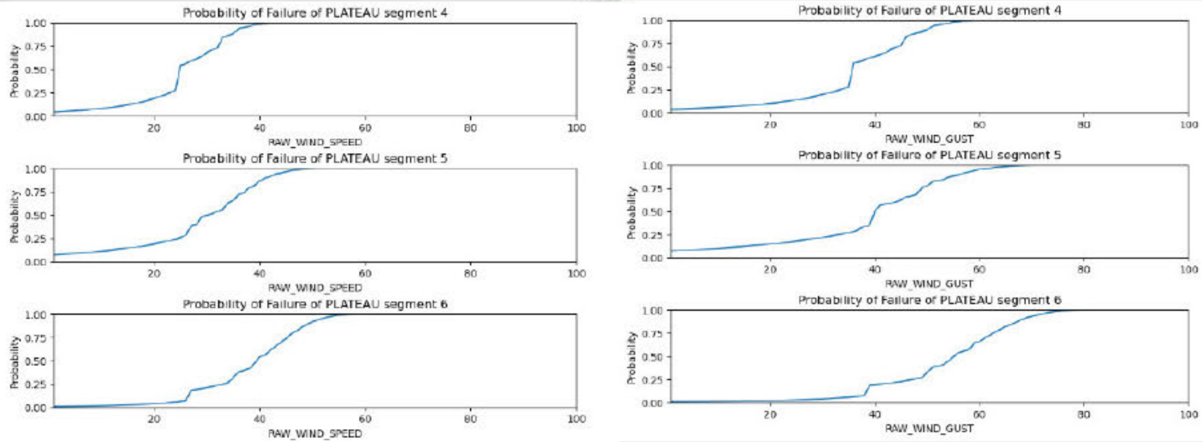


PATRIOT

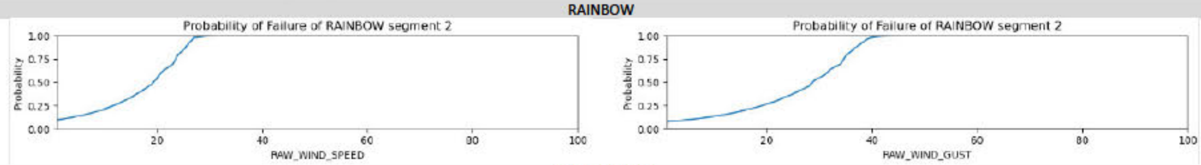




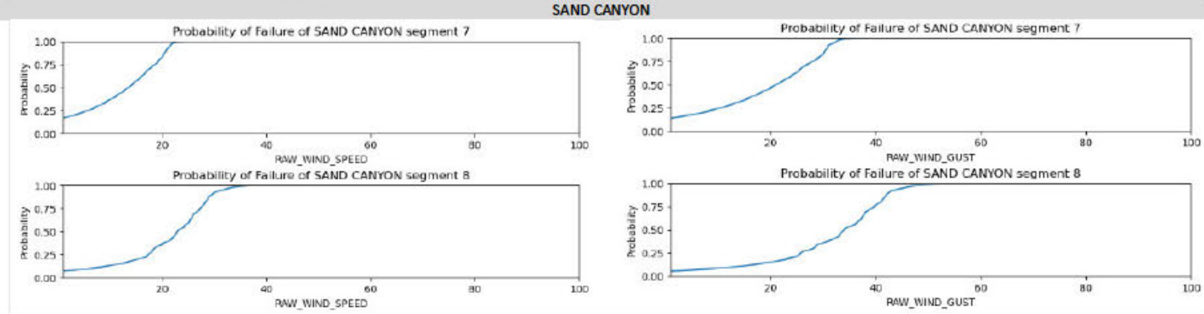
PLATEAU



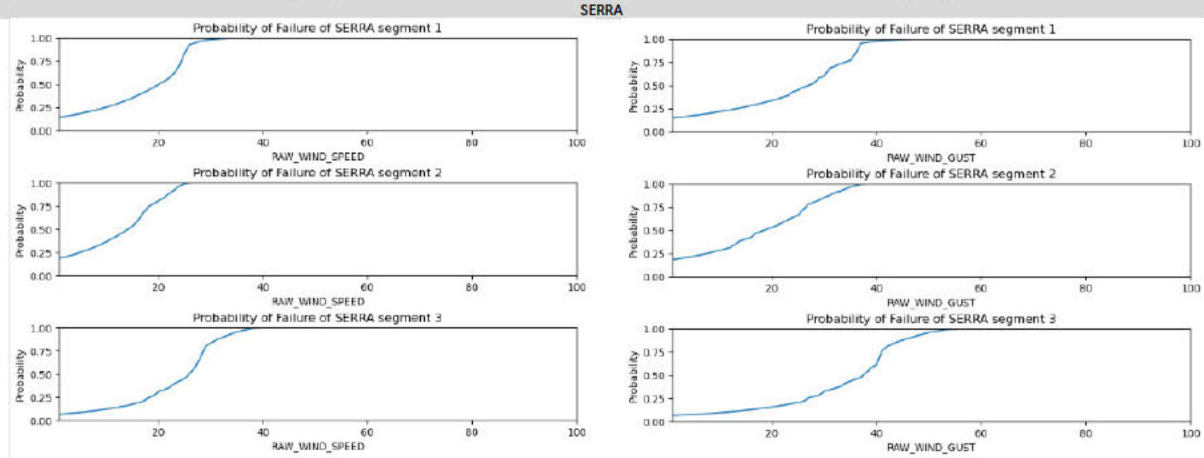
RAINBOW



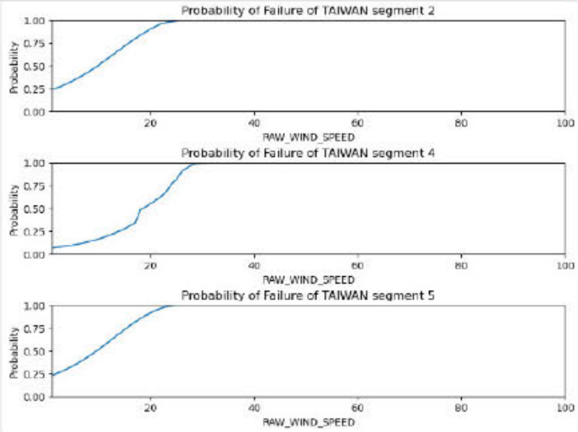
SAND CANYON

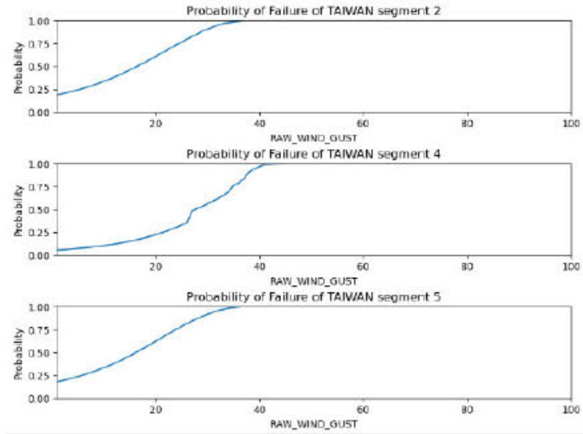


SERRA



TAIWAN


Probability of Failure of TAIWAN segment 2
Probability
RAW_WIND_SPEED
Probability of Failure of TAIWAN segment 4
Probability
RAW_WIND_SPEED
Probability of Failure of TAIWAN segment 5
Probability
RAW_WIND_SPEED


Probability of Failure of TAIWAN segment 2
Probability
RAW_WIND_GUST
Probability of Failure of TAIWAN segment 4
Probability
RAW_WIND_GUST
Probability of Failure of TAIWAN segment 5
Probability
RAW_WIND_GUST