

Southern California Edison (SCE)
Model Documentation
Prepared for 2026-2028 WMP
Appendix B

OH & Auto Switch Sub-Model

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1. EXECUTIVE SUMMARY

1.1 Model Purpose and Intended Use

The Overhead (OH) and Automatic (Auto) Switch Model is a Probability of Ignition (POI) Sub-Model developed by Southern California Edison (SCE). At SCE, models are developed using Machine Learning (ML) algorithms for each asset, i.e., OH Conductor, OH Switch, etc., and at each contact type level like animal, balloon, etc., as the drivers vary by asset and contact type. The OH & Auto Switch model is refreshed annually and used to predict the probability of failure (POF) for distribution OH and Auto switches.

The calibrated outputs of the OH & Auto Switch model—i.e., failure events—are broadly used by two categories of programs described below:

1. Inspections and Remediations programs that consider POI as an element in prioritization and scoping.
2. Risk analyses via SCE's Multi Attribute Risk Scoring (MARS) Framework.

1.2 Model Description Summary

The OH & Auto Switch model is a binary classification model using Random Forest—a ML technique. It predicts the probability of a switch igniting a spark due to equipment failure by considering available switch attributes and condition data (e.g., age, voltage) and other environmental and operational attributes (e.g., historical wind, switching counts).

The model is implemented in R programming using the library H2O and is connected to databases such as SAP, ADS Weather, etc. The model is run once a year manually by the Advanced Predictive Modeling team. The model is calibrated every year with the last 5 years of historical failure data.

Please refer to Section 2.1 for more information about the inputs used by the OH & Auto Switch model along with data processing details.

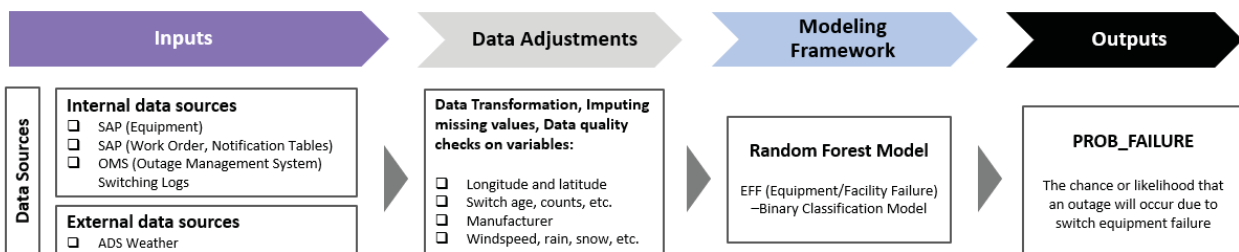


Figure 1: OH & Auto Switch model framework

The OH & Auto Switch model uses the Random Forest methodology. Since the prediction is a classified event (i.e., failure) and the Random Forest methodology can perform both classification and regression tasks, the Random Forest methodology is considered a good choice for the OH & Auto Switch model. This methodology predicts output with high accuracy, runs efficiently on large datasets, and maintains accuracy with minimal adjustments for missing values and data treatments.

1.3 Model Risk Rating

There is no defined mechanism to identify model risk rating at SCE. However, certain factors—like frequency of risk events and use case—are considered when flagging model risk. Based on the Wildfire Mitigation Plan quarterly report, the frequency of outages in a year from switches averages around 60. This frequency is low compared to other sub-drivers. **Error! Reference source not found.** provides a snapshot of the count of outages over the years by some Equipment/Facility Failure (EFF) sub-drivers, with switches in bold. In addition, the output of this model importantly informs the strategy of a few programs, discussed in section 1.1. Hence, the OH & Auto Switch model is deemed to be a medium risk model.

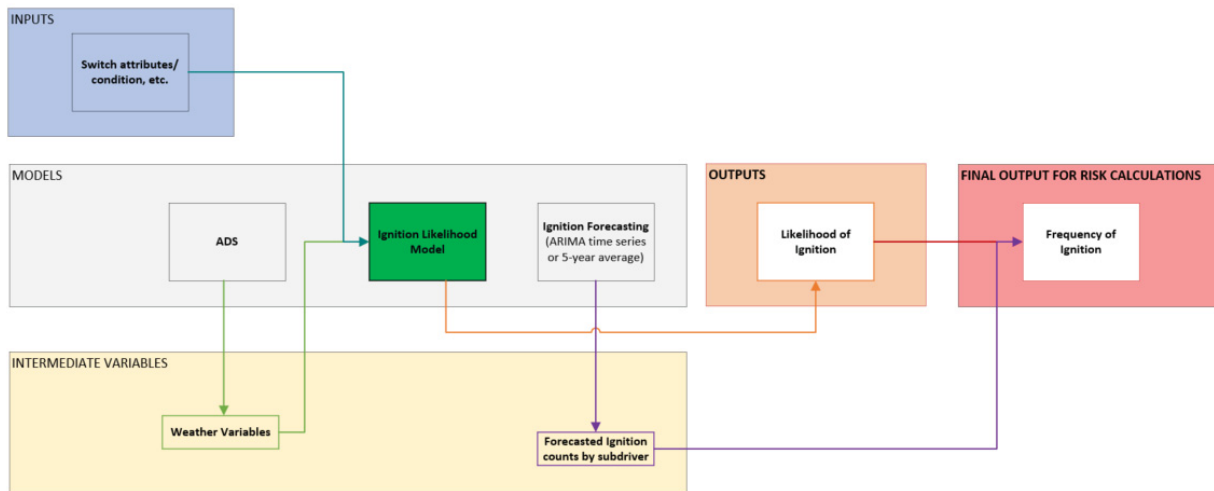
Table 7.1: Key recent and projected drivers of risk events			Number of risk events																Projected risk events							
Risk Event category	Cause category	Sub-cause category	2015	2016	2017	2018	2019	2020	2020	2020	2020	2021	2021	2021	2021	2022	2022	2022	2022	2023	2023	2023	2023	2023		
Outage - Distribution	18. Equipment / facility failure - Distribution	Capacitor bank damage or failure- Distribution	280	275	372	337	426	126	159	72	46	110	98	124	80	100	96	102	90	96	96	102	90			
		Conductor damage or failure — Distribution	463	594	654	713	1116	206	144	211	252	276	109	133	319	228	235	209	296	294	229	204	288			
		Fuse damage or failure - Distribution	232	195	245	508	1245	169	176	317	167	179	132	201	183	165	158	156	178	181	158	156	178			
		Lightning arrestor damage or failure- Distribution	105	127	99	106	216	27	21	26	25	12	21	18	22	8	26	24	27	24	26	24	27			
		Switch damage or failure- Distribution	51	46	45	67	78	17	11	16	19	14	10	18	22	10	13	16	19	15	13	16	19			
		Pole damage or failure - Distribution	98	126	130	207	541	57	36	31	40	32	22	21	60	32	47	43	56	52	47	43	56			
		Insulator and brushing damage or failure - Distribution	42	75	79	123	121	28	14	11	43	30	13	22	45	17	15	21	37	27	15	21	37			
		Crossarm damage or failure - Distribution	127	143	138	354	834	98	45	29	45	39	17	17	61	34	46	36	63	56	46	36	62			

Figure 2: Key recent and projected risk events due to switch damage or failure from SCE Q1 2022 Quarterly Data Report, Table 7.1

References: Refer to link [RF 1] in Section 5 for SCE’s Wildfire Mitigation Plan Q1 2022 Quarterly Data Report submission.

1.4 Model Dependency and Interconnectivity

The OH & Auto Switch model is an “Ignition Likelihood” model that uses Atmospheric Data Solutions (ADS) modeling output along with other data sources to calculate the probability of ignition.



***Ignition Likelihood model (highlighted in green) comprises of OH Switch model along with other POI models

Figure 3: Model Interconnectivity Schema

ADS weather variables are used as one input in the OH & Auto Switch model. ADS’ Next Generation Weather Modeling System (NGWMS) upgrades SCE’s in-house weather modeling capabilities and enhances SCE’s ability to make more targeted PSPS decisions. The ADS model generates 10 years of hourly

weather data between 2012 and 2022. That information is then processed and aggregated to calculate statistical measures such as mean and standard deviation of wind, humidity, rain, snow, etc. These are used as locational measures and are matched to the switches by their latitude and longitude coordinates.

The output data from the OH & Auto Switch model (i.e., POI) is used to inform the strategic decisions of the two categories of programs, discussed in Section 1.1.

1.5 Model Assumptions

The business and model assumptions for the OH & Auto Switch model are summarized below:

1. There is no change in the OH & Auto Switch technical specification over time.
2. The calibration methodology assumes that fires are a subset of failures.
3. The model is designed to work in both base weather and extreme weather conditions.
4. The feature variables in the dataset should have some actual values so that the classifier model can predict accurate results.
5. The predictions from each tree must have very low correlations.

A detailed explanation of these assumptions is available in Section 2.4.

1.6 Model Limitations

The model limitations for the OH & Auto Switch model are summarized below:

1. Unavailability of linear/non-linear representation in the form of intuitive equation or correlation statistic.
2. Time consumption for model execution is high.
3. Resource utilization in terms of system capacity and higher configuration for model execution is high.
4. Model accuracy may reduce if the dataset experiences covariate shift.

A detailed explanation of these data limitations is available in Section 2.5.

1.7 Overall Model Performance Assessment

The ML model used to build the OH & Auto Switch model is the Random Forest algorithm. The model's overall performance is determined by the Area Under the ROC Curve (AUC) value and Confusion Matrix results.

The performance of the OH & Auto Switch model was evaluated on test data using historical failure information between 2019-2023.

- The AUC value is 0.78.
- Confusion matrix results capture the accuracy rate as 82.2%.

The above metrics were derived at the time of the model refresh in September 2024 to capture an exhaustive set of statistical results for documentation purposes.

1.8 Contingency Plan for Vendor Model

A contingency plan is not applicable for this model as it is an in-house SCE model. This is not a vendor model.

2. MODEL FRAMEWORK AND THEORY

The OH & Auto Switch model is a binary classification model pertaining to switch equipment failures. It employs a random forest algorithm to predict the likelihood of a switch experiencing a failure that can result in an ignition event. The random forest approach was chosen for the classification task over other modeling approaches—such as gradient boosting, etc.—because it predicts output with high accuracy, runs efficiently on large datasets, and maintains accuracy with minimal adjustments for missing values and data treatments.

2.1 Model Inputs and Data Quality

Data Sources

This model refers to multiple internal and external data sources. The internal data sources used by the model are:

- **SAP** houses circuit¹, structure, and equipment characteristics. It contains latitude and longitude information of the assets. SAP also houses notification and work order records which track completed work for issues like repairs, replacements, etc. The latter is used to develop failure targets for the model.
- **OMS** refers to Outage Management System which contains information about switching operations and about switch assets including latitude and longitude as well.
- **Net9** is built on GESmallWorld data and MAP3D data. GESmallWorld contains all the asset attributes of conductors along with the connectivity of structures and segments. MAP3D is used for geospatial display, and it contains the geospatial attributes of the assets. Net9 is used to get downstream kVA and Short Circuit Duty values at the switch locations.
- **Short Circuit Duty (SCD) datamart** is a consolidated dataset built on Integrated Capacity Analysis and Net9. It provides segment-level SCD values across the territory. SCD represents the current that equipment experiences during a fault, indicating the stress on the equipment and its ability to clear faults quickly.

The external data sources used by the model are:

- **ADS** model provides 10 years of hourly gridded weather data from 2012-2022. These are aggregated to individual locational measures and matched to the switches through spatial join to the nearest grid by the latitude and longitude as a part of the data engineering step.

Quality Checks

SCE has internal data management teams for ensuring data quality, including Enterprise Asset Data (EAD) and Master Data. They work on processing asset data corrections (E2 notifications) in SAP and fixing largely known data issues like missing or erroneous latitude and longitude information for assets in the territory. Some of the data quality checks performed in the OH & Auto Switch model to ensure accuracy, validity, integrity, and consistency are provided below. Quality checks (QC) are coded in R and incorporated into the data gathering process.

¹ Circuit comprises a collection of segments that altogether form a path for electrical current floating from the power source (including but not limited to a substation) to another power source or circuit endpoint.

The QC steps performed by automated R code are as follows:

- Duplicate records that are identified in the switching operations log are removed to maintain consistency in counting times operated by considering only the distinct records including date stamp.
- SAP includes all historical equipment records. The most recent record for each equipment is selected to filter out inactive records if a replacement occurred.
- SAP provides information about all the removals and remediations encountered by SCE. Only the relevant failures specific to switches are loaded into the respective model. All the other non-relevant information, i.e., for equipment other than switches, is excluded.

The manual QC steps are as follows:

- ADS weather data is validated against actual weather observations.
- Asset data obtained from SAP is validated and updated through inspections and other programs.

Data Sampling

Since this is a classification model to predict switch failures, there are no sampling strategies used in the model other than the random split strategy to bifurcate the train and test data. The dataset used for the model is randomly divided to have 80% in train data and 20% in test data.

Data Cleansing and Transformation

The data cleansing and transformation activities that are incorporated in the R scripts as a part of automation to ensure the completeness of data used for model training and estimation are provided below.

- Missing data in SAP for the below specified numeric variables are handled by referring to another database, OMS
 - latitude
 - longitude
- The asset's manufacturer is not always populated so values are imputed for this feature with help of information in other variables like switch subtype.
- Data consistency is ensured by correcting formatting issues in date variables. For example, Start-Up Date variable can have different formats of data and is corrected in R by forcing the values to a consistent day, month, year format.

Data Assumptions

The accuracy of the predicted results is dependent on the accuracy of the data used to build the predictive models. The data assumptions follow:

1. The assumptions for the data imputation uses SCE's Distribution Design Standard (DDS), engineering judgment, and manufacturer data.
2. The target labeling process used to label the failures and non-failures as '1' and '0' is considered accurate. This is performed by observing historical failure records. If the switch experiences a removal, replacement, or repair within the study period (2019-2023) then '1' is assigned to represent failure. Else '0' is assigned for non-failures.

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3. Input data with respect to asset, weather, and engineering information are assumed to be stable and will not change over time until the subsequent data refresh. For example: If there is an update in the structure information specific to an asset, that updated information will be reflected only in the subsequent data refresh. So it is assumed that the updated structure information is not drastically different from the previous information and would not alter the model outcomes.

Data Limitations

The following are data limitations across internal and external data sources:

Some of the data used by the model faces accuracy issues in terms of consistency in data labeling or missing values that may impact model prediction power.

- Data labeling issues may be caused by manual errors during data entry. For example, when manufacturer information is fed manually into the system, different labels for the same manufacturer might be used in different data entries. This affects the consistency of the data and needs to be addressed before using the data in the model.
- Missing data for a specific feature (predictive variable) might be due to unavailability of data. For example, for the switching counts feature, some planned work and energized operations like fully operated load and load drops at lesser currents are not tracked. To overcome this issue, recorded switching counts pulled from OMS are used as a proxy to estimate times operated which is further used in model processing. Other missing values for a switch are filled using imputations by cross-referencing other fields or other data sources to mitigate the risk arising from missing predictors.

Independent variables

The OH & Auto Switch model uses multiple variables/features. A subset of the independent variables used in the OH & Auto Switch model, along with its data source and description, is provided below.

Feature	Data Source	Description
eq_sys_voltage_UDF	SAP	Voltage handled by the equipment
SCD	SCD datamart	Short Circuit Duty. Represents amount of fault current at that location
DOWNSTREAM_KVA	Net9	Downstream kVA. Represents capacity
AGE_UDF	SAP	Calculated age of switch equipment, from start-up date to the beginning of forecast period (2024)
oms_switching_cts	OMS	Counted # of times the switch was operated. An operation is either open or close.
manufacturer_UDF	SAP	Manufacturer of the switch
region_UDF	SAP	Region where the switch resides
ASSET_SUBTYPE_UDF	SAP	Switch asset subtype (Accessory or Pole Disconnect, Dip, Horizontal, Tiered, Triangular, Vertical)
ASSET_TYPE_UDF	SAP	Switch asset type (Loadbreak, Non-loadbreak)
control_type_UDF	SAP	Switch control type (Manual, RCS)

In addition to the data above, 10 years of hourly data fetched from ADS Weather model is processed and aggregated to calculate statistical measures like mean, max, and standard deviation for wind, temperature, cloud fraction, shortwave flux, rain, and snow.

Dependent Variable

In a typical classification risk model, defining the dependent variable is key for both model development and model performance assessment. The dependent variable in the OH & Auto Switch model represents the observation of a switch equipment failure in terms of removals, replacements, or repairs. It is a binary status of failure or non-failure.

The final output of the model is `PROB_FAILURE`, representing the chance or likelihood that a switch failure will occur. The `h2o.predict (level = 0.05, type = 'response')` function is used to specify the desired output (`PROB_FAILURE`) in probability values, rather than binary values. The probability value ranges from 0 to 1 where '0' represents the least likelihood of failure and '1' represents high chance of failure.

2.2 Methodology

SCE uses ML to identify patterns that may lead to failures causing sparks from switches and uses the trained model to predict Probability of Ignition (POI)s at the asset level. The OH & Auto Switch model employs a random forest algorithm to predict failure events.

A random forest is a supervised ML algorithm that is constructed from many decision trees. It can be used to solve both classification and regression problems. This approach uses ensemble learning, which is a technique that combines many classifiers to achieve greater predictive accuracy than that of a single classifier. A decision tree is a decision support technique that forms a tree-like structure. It consists of three components: decision nodes, leaf nodes, and a root node. The following diagram shows the three types of nodes in a decision tree.

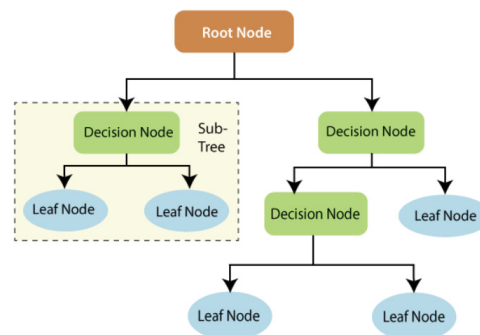


Figure 4: Decision Tree Structure

A decision tree algorithm divides observations of a dataset into branches, which further segregate into other branches. This sequence continues until a leaf node is attained. A leaf node cannot be segregated further. In more detail, the root node is the base of a decision tree, where the first of a chain of decisions is made. A branch is the connection path between nodes. A node is a potential splitting point on a tree. Decision nodes provide a link to the leaves. On the other hand, leaves, also known as terminal nodes, are the ends of a tree, representing the resulting classification or value for the sample.

The 'forest' generated by the random forest algorithm is trained through bagging, also known as bootstrap aggregating. Bagging is an ensemble meta-algorithm that fits multiple models on different subsets of a training dataset and then combines the predictions from all models. The diagram below shows a simple random forest classifier.

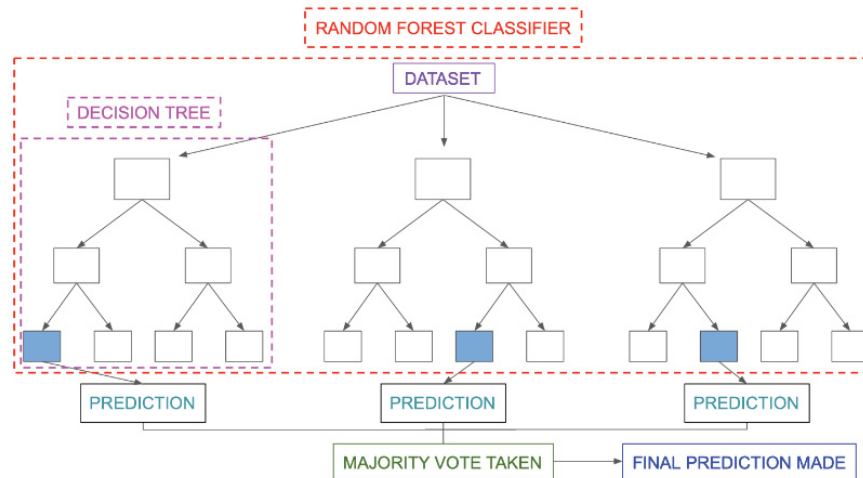


Figure 5: Structure of Random Forest Classifier model

The selection of the final output follows a majority-voting system. In this classification model case, the output chosen by a majority of the decision trees becomes the final output of the random forest system. The greater number of trees in the forest leads to higher accuracy and prevents the problem of overfitting.

Train test split is a model validation procedure that simulates how a model would perform on new/unseen data. Figure 6 shows the logic for dividing the dataset into train data and test data. First, the data is consolidated and prepared for train test split. Then the historical input datasets are split into a training dataset (80%) and testing dataset (20%) based on simple random sampling strategy with a split ratio of 4:1 without replacement. Simple random sampling is a technique that ensures each observation has an equal likelihood of being selected for a set. It is a fair strategy as it helps in avoiding any bias involved compared to other modeling techniques and it has no restrictions on the sample size which makes it suitable to handle vast amounts of input data. The predictive algorithm is developed using the training dataset and built by looking at the interactions between all the features to find patterns and predict the likelihood of equipment failure.

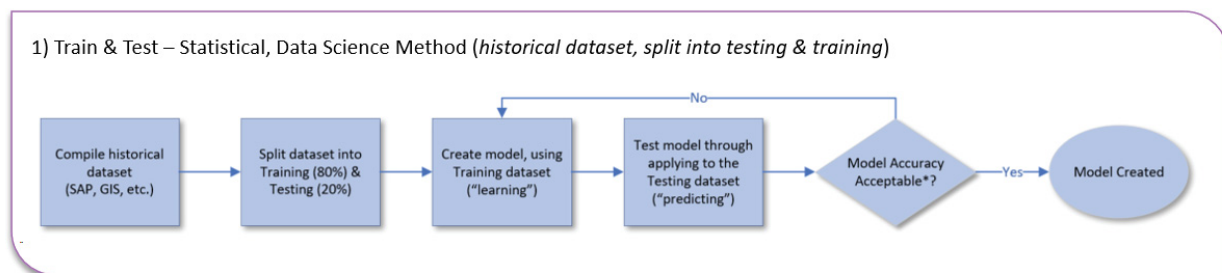


Figure 6: Train and Test data split logic

In the next step, the algorithm is tested on the ‘testing’ dataset. The model is run on the test dataset to make a prediction of a failure or success. Then an internal validation of the model is conducted by comparing the predicted results to the actual results which indicates the predictive capabilities of the features as well as the model. Area Under the Curve (AUC) is the metric used to assess the performance of the model on test data.

AUC – Area Under the Receiver Operating Characteristic (ROC) Curve estimates the model discriminatory power (i.e., degree of separability) for the binary classification problem. The ROC curve plots True Positive Rate against different thresholds with False Positive Rate (FPR) or True Negative Rate (TNR). The higher the AUC, the better the model is at predicting True Negatives (non-events) and True Positives (events).

Hyperparameter Tuning:

Hyperparameters are parameters that are explicitly defined by the user to control the learning process. The process of selecting the optimal hyperparameters to use is known as hyperparameter tuning, and the tuning process to achieve the best-defined performance statistic is known as hyperparameter optimization. Cartesian Grid search and Random Grid search are widely used strategies for hyperparameter optimization.

- In the Cartesian grid search approach, the ML model is evaluated for a range of hyperparameter values, and it searches for the best set of hyperparameters from a grid of hyperparameters values. The disadvantage of grid search model is that it will go through all the intermediate combinations of hyperparameters which increases the time consumed by grid search computations.
- In the random grid search approach, the ML model is evaluated for a range of hyperparameter values like that in Cartesian Grid Search approach. However, search criteria parameters are added to control the type and extent of the search, and it moves randomly within the grid to find the best set of hyperparameters to achieve maximum performance in terms of the metric defined by the user. As search criteria, the user can set a maximum runtime for the grid, a maximum number of models to create, or metric-based automatic early stopping. If many of these requirements are supplied, the algorithm will end when the first of the criteria is met. This approach reduces the time taken for computation thereby solving the drawbacks of the cartesian grid search approach.

The OH & Auto Switch model uses Random Grid Search method for Hyperparameter tuning. The reference literature link to understand the efficiency between Cartesian Grid search and Random Grid search is provided below. The criterion used for the hyperparameter tuning in OH & Auto Switch Model are:

- **ntrees:** Total number of trees used in the random forest. For tuning this parameter, the OH & Auto Switch model uses a range of values between 100 and 500 with an increment of 50.
- **mtries:** Total number of predictors/variables that will be randomly selected in each node to search for the best split. This parameter is varied by using different percentages of the total number of independent variables in the model. The various percentages taken into account are 5%, 15%, 25%, 33.3%, and 40%.
- **max_depth:** The maximum number of decision splits allowed within a tree. A higher value for this feature will make the model more complex and can lead to the issue of overfitting the training data. For the max_depth parameter tuning, the range of values used for the OH & Auto Switch model are set between 25 and 50 with an increment of 5.

- `min_rows`: This parameter defines the minimum number of observations required for a leaf to split. This parameter is tuned using the values 1, 2, 7, 10, and 15.
- `Sample_rate`: The percentage of the sample data drawn for training each tree. The scale goes from 0 to 1.0. This parameter is tweaked with values of 0.5, 0.632, 0.7, and 0.8.

Random Grid Search method uses the below specified stopping criterion in the OH & Auto Switch model to stop the random grid search. The conditions are provided below.

- `stopping_tolerance = 0.005`
This will stop the random search if the tolerance level reaches 0.005.
- `stopping_rounds = 15`
This will stop the random search if none of the last 15 models managed to have 0.5% improvement compared to best model identified before that.
- `max_runtime_secs = 3600`
This is used to define the maximum number of seconds allowed for the search. The random search will stop if the search continues to find improvements after 30 min.
- `stopping_metric = AUC`
This defines the performance metric-based condition to stop the search. The random grid search will stop when the model's AUC value doesn't improve by 0.5% for the OH & Auto Switch model.

Once the random search is complete, the grid object containing the list of models is queried, and models are sorted by a performance metric defined by the user. The model with better performance is chosen as the best model and it is validated on the test data.

References: Refer to [\[RF 2\]](#) in Section 5 to understand the efficiency between Cartesian Grid search and Random Grid search.

2.3 Suitability

During development of the model in 2017, Gradient Boosted Machine (GBM) was used to construct the OH Switch model. Then Random Forest, another modeling approach, was tested. The test results proved that the Random Forest methodology fits well for the OH Switch model as it exhibited similarly high AUC as other approaches. See Section 3.4 for the AUC comparison of these two approaches.

Random Forest methodology can be used to solve both classification as well as regression problems and it can handle both categorical and continuous variables. One of the main advantages of the Random Forest methodology is that it maintains accuracy with minimal adjustments for missing values and data treatments. The Random Forest methodology provides a high level of accuracy and stability and handles non-linear parameters efficiently. Additionally, hyperparameter optimization prevents the issue with random forests overfitting. Random grid search is used for hyperparameter tuning; it controls the maximum depth of the sample data drawn for training each tree and involves stopping criterion which reduces the computation time.

Hence, the use of Random Forest for the OH & Auto Switch model is deemed to be a suitable fit.

2.4 Assumptions

The key business assumptions that were considered during model development are specified below:

BA 01: There is no change in OH & Auto Switch technical specification over time. The model assumes the type of OH & Auto switches used in the model building process have the same characteristics in terms of build and quality. For example, each switch asset type generally has its unique technical specifications, like physical attachments and mounting direction, that are expected to remain the same over time.

BA 02: The Calibration model assumes that fires are a subset of failures. Failures prompting the need for removals, replacements, and repairs are the representative failure targets used in place of few ignition events. Some of these issues left unaddressed can potentially spark an ignition, but not all failures will result in a fire. Hence, fire can be treated as a subset of failure.

BA 03: The model is designed to work in both base weather and extreme weather conditions. The weather variables incorporated in the model are represented as various statistical aggregations like max, mean, and standard deviation on wind, wind speed, humidity, rain, and snow. Hence the model results can be used under both base weather and extreme weather conditions.

The functional/model methodology assumptions that were considered during model development are discussed in detail below:

MA 01: The feature variables in the dataset should have some actual values so that the classifier model can predict accurate results. In an ideal scenario, all variables would have actual, not estimated, values. The current model provides accurate results even after using estimates as they are derived through imputation using actual values from other variables. Example: Inferring manufacturers based on switch subtype.

MA 02: The predictions from each tree must have very low correlations. It is difficult to differentiate between a real interaction effect, marginal effects, and random variations in random forests. Hence, the presence of highly correlated variables in the Random Forest approach will have an impact on its ability to identify strong predictors.

2.5 Limitations and Compensating Controls

The key model limitations that would impact the accuracy and performance of the model are discussed in detail below:

Limitation ID: L01

Limitation Title: Unavailability of linear/non-linear representation in the form of intuitive equation or correlation statistic.

Description: The Random Forest algorithm does not explain any linear or non-linear relationship in the form of an intuitive equation or correlation statistic to enable measurement of the scalability of impact of independent variables on the dependent variable.

Compensating Controls: The Random Forest model is considered a black box as it is difficult to understand the relationship between independent and dependent variables and how the independent variables influence the predictions. Since black box is a common limitation with most ML algorithms, usage of the model is considered appropriate as it provides better AUC results than other models.

Limitation ID: L02

Limitation Title: Time consumption for model execution is high.

Description: Since Random Forest models use a bagging algorithm, they can provide more accurate predictions but slow down the process as they compute data for each decision tree.

Compensating Controls: To overcome the time consumption issues from grid search computations, random grid search is used in the hyperparameter tuning process. Random grid search is a proven technique to reduce the time consumption when testing multiple models with different combinations of hyperparameters by using stopping criterion like tolerance, maximum rounds, maximum run time, and performance improvement thresholds. It moves within the grid in a random fashion to find the best set of hyperparameters to achieve maximum performance in terms of the metric specified, here AUC. Since the model is not executed through computer program automatically at a defined frequency and is instead run only once a year manually, usage of the model is considered appropriate.

Limitation ID: L03

Limitation Title: Resource utilization for model execution is high.

Description: Since Random Forest models process many decision trees, they need more resources with respect to system configuration and system capacity to store that data.

Compensating Controls: The resource utilization factor will have a major impact for real time models as they would run more frequently. Since the OH & Auto Switch model is run only once a year with reasonable use cases, the impact of resource utilization is low. Additionally, the usage of random grid search and stopping criterion like tolerance, maximum rounds, maximum run time, and performance improvement thresholds provide more control on the number of recurring instances run to identify the best fit hyperparameters to achieve optimal AUC. Since the model is not executed through computer program automatically at a defined frequency and is instead run only once a year manually, usage of the model is considered appropriate.

Limitation ID: L04

Limitation Title: Model accuracy might reduce if the dataset experiences covariate shift.

Description: Covariate shift is a type of model drift that occurs when the distribution of independent variables changes between the training environment and live/test environment. Since the Random Forest cannot extrapolate (i.e., predict outside the training space), the model performance might decrease if there is covariate shift in the dataset.

Compensating Controls: The covariate shift affects most ML models to some degree, as test data is never going to be the same as training data. Detecting and addressing covariate shift is therefore a key step to the ML process. The current model is run only once a year along with data refresh. It uses a random sampling mechanism to split the dataset into train (80%) and test (20%) data whenever it is run. The

random sampling mechanism is used to resolve covariate drift and maintain the accuracy of model results. Hence the usage of the Random Forest methodology along with the random sampling mechanism to split train/test data is considered appropriate.

2.6 Model Outputs

The OH & Auto Switch model predicts the probability of ignition (POI) arising from equipment (switch) failure. The model has a single output characterized by a continuous number between 0 and 1 for each OH & Auto Switch asset.

The probabilities across different asset failure predictive models cannot be aggregated or compared and hence are calibrated to derive frequencies of ignition. The sum of the resulting frequencies of ignition for a sub-driver equals the total expected ignitions for the specified year.

$$\text{Frequency of Ignition} = \text{Probability of Ignition} \times \frac{\text{Calibrated Targets}}{\sum \text{Probability of Ignition}}$$

where Calibrated Targets = Forecasted Ignitions for that sub-driver

The output from this calibration exhibits the following features:

- Frequency: Each value can be specified as the frequency of fires per year.
- Comparability: The frequencies are comparable against sub-drivers and models.
- Additivity: The frequencies can be added across models to derive the aggregated fire forecast in a year.

This is achieved by forecasting fires by sub-driver and using these forecasts to weight the model probabilities. The sum of probabilities from each calibrated model equals the forecast by sub-driver.

Figure 7 provides the calibration steps that are performed using the failure probability results from the OH & Auto Switch model. The methodology followed in the calibration model is provided below:

- A. Aggregate the probability output from each sub-driver model.
- B. Based on the forecast logic selected, find the forecast results (i.e., expected fires) for each sub-driver.
- C. Generate the calibration factor for each sub-driver based on the values calculated in the above steps (B/A).
- D. Multiply each model probability by its calibration factor to arrive at the estimated frequency of fires from each sub-driver.

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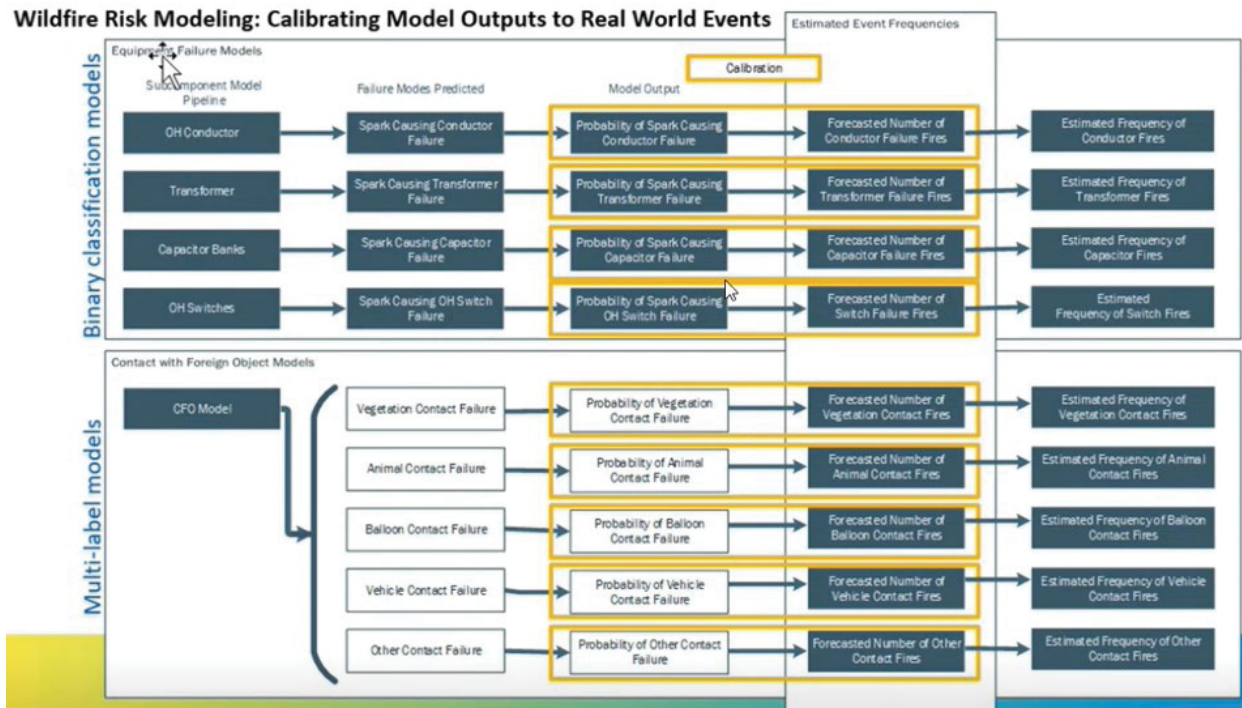


Figure 7: Calibration model schema

This estimated frequency of fires from each sub-driver can be added across the models to derive the expected frequency of ignition for each location.

The data from the calibrated probabilities—frequencies of events—based on the output from the OH & Auto Switch model is used to inform the programs mentioned in Section 1.1.

Model Changes:

The OH Switch model was enhanced with the following changes in June 2022 as part of the annual refresh:

- Replaced weather features to incorporate more granular (hourly, 2km x 2km gridded) ADS weather data; was previously referring to weather station observations that generalized larger territorial regions
- Filled in unknown manufacturer names by using vendor numbers and by referring to switch subtype
- Expanded failure dataset to include repairs and replacement notifications in addition to removals that were initially tracked

In August 2023, the OH Switch model was modified to include both manual and automatic switches—resulting in the OH & Auto Switch model. Other enhancements include:

- Filled in district and region information for previously incomplete entries
- Referenced the latest notification and equipment data

In September 2024, the OH & Auto Switch model was enhanced with the following updates:

- Added control_type feature to indicate Manual/RCS switch

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OH & Auto Switch Sub-Model

- Revised oms_switching_cts to consider the installation date of the switch and availability of OMS data
- Added SCD feature to represent amount of fault current at that location
- Added downstream kVA to represent capacity
- Refined scope of notifications to be considered in the failure targets

The AUC value of the OH & Auto Switch model was 0.78 after refresh.

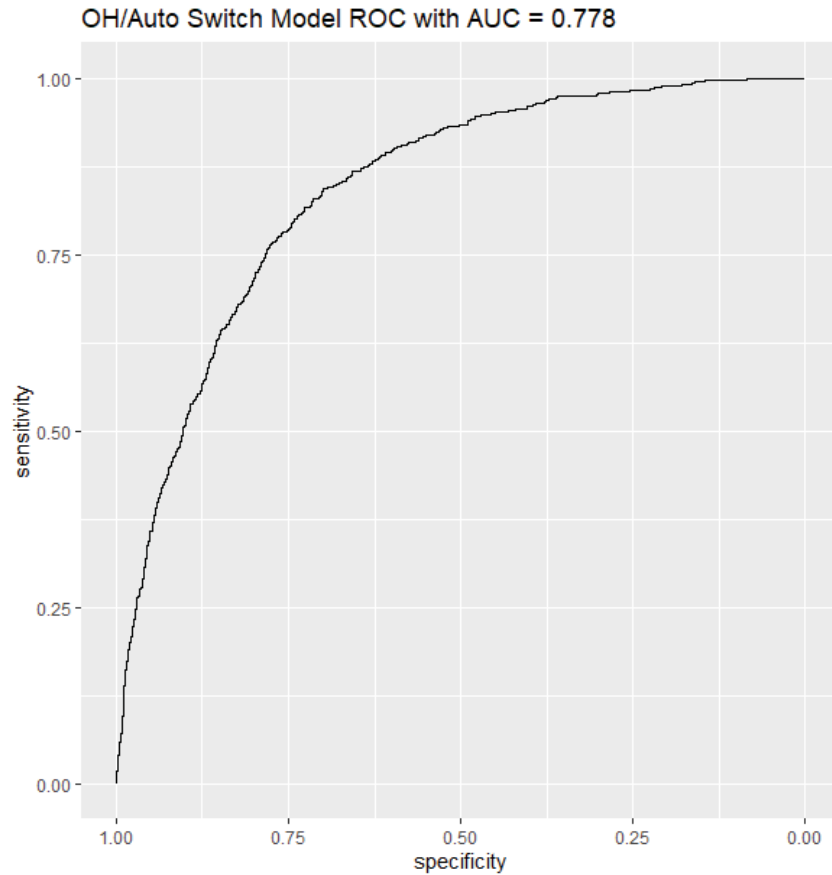


Figure 8: AUC results for OH & Auto Switch model after refresh

3. MODEL PERFORMANCE AND TESTING

For each ML model developed, SCE tries to select the best algorithm based on the model train/test performance, which can be measured by Area Under the Curve (AUC) and other metrics from the Confusion Matrix.

3.1 Model Specification Testing

The model is developed and tested in R programming using library H2O. The model is run once a year manually by Advanced Predictive Modeling team. The model is calibrated every year with the last 5 years of historical failure data.

SCE performs verification of the model implementation by checking the variable importance results (see Model Estimation section below for a detailed explanation of variable importance results). The performance of the model is validated through the AUC, defined in Section 2.2 and provided in Section 3.3.

The validity and impact of the Model Assumptions, mentioned in Section 2.4, are discussed below:

- The features used in the model are expected to have some actual values so that the model results can be accurate. In an ideal scenario, all the variables would not have estimated values and they would instead use actual values. Some features like manufacturer do not have the actual values in all scenarios so values are imputed for this feature with help of information in other variables like switch subtype. After using these estimates, the data quality is enhanced to support reliability of the current model in terms of improved predictive accuracy.
- Random Forest is considered a strong approach for variable selection in high-dimensional data only when the variables have low correlation. The recursive structure of trees generally enables them to take dependencies into account in a hierarchical manner. However, some variable combinations without clear marginal effects might make the tree algorithm ineffective. To conclude, it is difficult to differentiate between a real interaction effect, marginal effects, and just random variations in random forests. Hence, the presence of highly correlated variables in Random Forest approach will have an impact on its ability to identify strong predictors. Adequate measures are taken to filter out highly correlated features to overcome their impact in predicting the results.

Model Estimation:

The OH & Auto Switch model employs several independent variables. Section 2.1 contains a list of the independent variables utilized in this model.

The variable importance test results for the OH & Auto Switch model, Figure 9, shows the order of which features provide the most information gain in informing the correct prediction of failure or non-failure. The variable importance features test estimates the relative influence of each variable by calculating whether that variable was chosen to split during the tree building process and how much the squared error over all trees improved, or decreased, as a result.

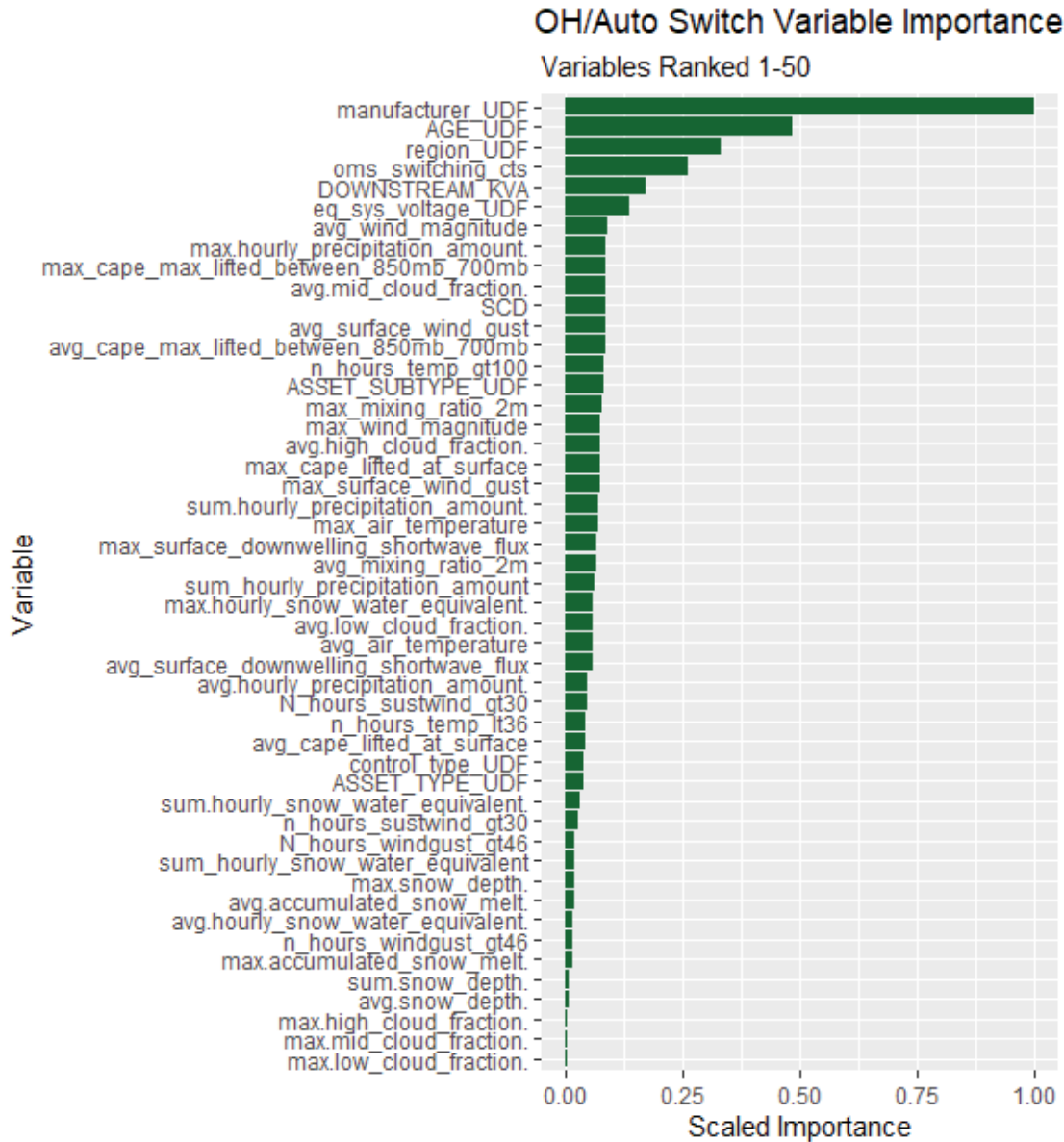


Figure 49: Variable Importance test results for the OH & Auto Switch model

The results confirm that the features manufacturer_UDF, age_UDF, and region_UDF exhibit high importance on the OH & Auto Switch model output.

References: Refer to link [\[RF 3\]](#) in Section 0 for description on the methodology used to perform the Variable Importance for tree-based methods.

The OH & Auto Switch model uses the random grid search approach for hyperparameter optimization to select the best set of hyperparameters to achieve maximum performance in terms of AUC as described in Section 2.2. Once the grid search is completed, a list of models with their associated hyperparameter values is obtained as shown in Figure 10. The acquired models are then sorted based on the AUC values. The model with the highest AUC value is regarded as the best fitted model. Figure 11 shows the best

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model obtained for the OH & Auto Switch model. The best model is run on the respective test data, and the AUC metric is used to evaluate the model performance.

The AUC is used to estimate the model discriminatory power to predict the results in a binary classification problem. A higher AUC means the model can predict the results more accurately. Figure 13 shows the ROC with AUC for the OH & Auto Switch model based out of test dataset ran with the last 5 years of historical failure data (2019-2023) (results derived in Sept 2024 R scripts re-rerun). The AUC value for the OH & Auto Switch model is 0.78.

```
Grid ID: Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867
Used hyper parameters:
- max_depth
- min_rows
- mtries
- ntrees
- sample_rate
Number of models: 99
Number of failed models: 0

Hyper-Parameter Search Summary: ordered by decreasing AUC
max_depth min_rows mtries ntrees sample_rate model_ids auc
1 25.00000 15.00000 19.00000 500.00000 0.70000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_73 0.78328
2 50.00000 10.00000 19.00000 250.00000 0.50000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_48 0.78326
3 35.00000 15.00000 19.00000 300.00000 0.70000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_40 0.78286
4 50.00000 15.00000 19.00000 450.00000 0.50000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_90 0.78281
5 45.00000 10.00000 19.00000 300.00000 0.70000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_30 0.78273

---
max_depth min_rows mtries ntrees sample_rate model_ids auc
94 30.00000 1.00000 2.00000 350.00000 0.50000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_64 0.70093
95 40.00000 1.00000 2.00000 150.00000 0.70000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_58 0.69125
96 50.00000 1.00000 2.00000 250.00000 0.80000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_54 0.68738
97 45.00000 1.00000 2.00000 500.00000 0.80000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_32 0.68669
98 45.00000 1.00000 2.00000 450.00000 0.80000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_57 0.68647
99 50.00000 1.00000 2.00000 450.00000 0.80000 Grid_DRF_TRAIN_3Y.hex_model_R_1727940215182_6867_model_26 0.68638
```

Figure 10: List of models with their associated hyperparameter values produced after the grid search for the OH & Auto Switch model

```
Model Details:
=====
H2ObinomialModel: drf
Model ID: Grid_DRF_TRAIN_3Y.hex_model_R_1724839089198_14078_model_31
Model Summary:
number_of_trees number_of_internal_trees model_size_in_bytes min_depth max_depth mean_depth min_leaves max_leaves mean_leaves
1 500 500 4159724 20 33 25.17600 387 689 655.58200
```

Figure 5: The best model selected for the OH & Auto Switch model, along with the related hyperparameter values.

In terms of model convergence, the random grid search for hyperparameter tuning uses a stopping criterion based on a specified tolerance in AUC. This means that the additional efforts involved in hyperparameters tuning and training is not likely to improve the model performance beyond the specified threshold.

The accuracy of the model prediction, in addition to AUC, can be determined using the Confusion Matrix and Classification Error Rate results.

- A Confusion Matrix presents a tabular layout of the different outcomes of the predicted and actual values of a classifier model.

OH & Auto Switch - Confusion Matrix Results				
Actuals	Predicted			Error Rate
	0	1		
	0	5038	909	0.152850
	1	299	538	0.357228
		5337	1447	0.178066

- Table 1: Confusion matrix results for OH & Auto Switch model

OH & Auto Switch - Confusion Matrix Results				
Actuals	Predicted			Error Rate
	0	1		
	0	5038	909	0.152850
	1	299	538	0.357228
		5337	1447	0.178066

- Table 1 provides the Confusion Matrix results for OH & Auto Switch model. It captures the accuracy rate as 82.2%.
- Classification error rate is used to estimate the proportion of instances misclassified over the whole set of instances. It is estimated using the below formula.

$$\text{Error Rate} = \frac{\text{False Positives} + \text{False Negatives}}{\text{True Positives} + \text{True Negatives} + \text{False Positives} + \text{False Negatives}} * 100$$

The error rate for OH & Auto Switch model turns out to be 17.8%. This means that the failure rate of the model prediction is moderately low and under control.

All these test results are performed on test dataset with historical failure information between 2019-2023.

A detailed assessment of the model limitations and associated compensating controls is available in Section 2.5.

3.2 Sensitivity Analysis

Shapley Additive Explanations (SHAP) is a method that provides an explanation of a model's output by attributing the contribution of each feature to the model's prediction. SHAP is based on the concept of Shapley values, which is a method for distributing the contribution of each player in a cooperative game. In the context of a ML model, the players are the features, and the game is to predict the output. For sensitivity analysis, SHAP values were calculated for the input features to quantify how each feature impacted model predictions.

To calculate the Shapley values for a feature, SHAP generates a set of all possible feature combinations, called coalitions. For each coalition, SHAP calculates the model's output and the difference between the output of the coalition with and without the feature. These differences are averaged over all possible coalitions, giving a measure of the feature's contribution to the model's prediction. This process is repeated for each feature in the model.

The result is a set of Shapley values that describe the contribution of each feature to the model's prediction. Positive Shapley values indicate that the feature increases the model's prediction, while negative values indicate that the feature decreases the prediction. The magnitude of the Shapley value indicates the importance of the feature. These values can be used to provide an explanation of the model's output, either by showing the contribution of each feature for a specific prediction or by

calculating the average contribution of each feature over the entire dataset. By transforming variables into additive factors that drive probability, SHAP can analyze the sensitivity of a model to different variables, which can help identify which features are the most important in making predictions. Overall, SHAP provides a powerful method for understanding and interpreting the behavior of complex ML models.

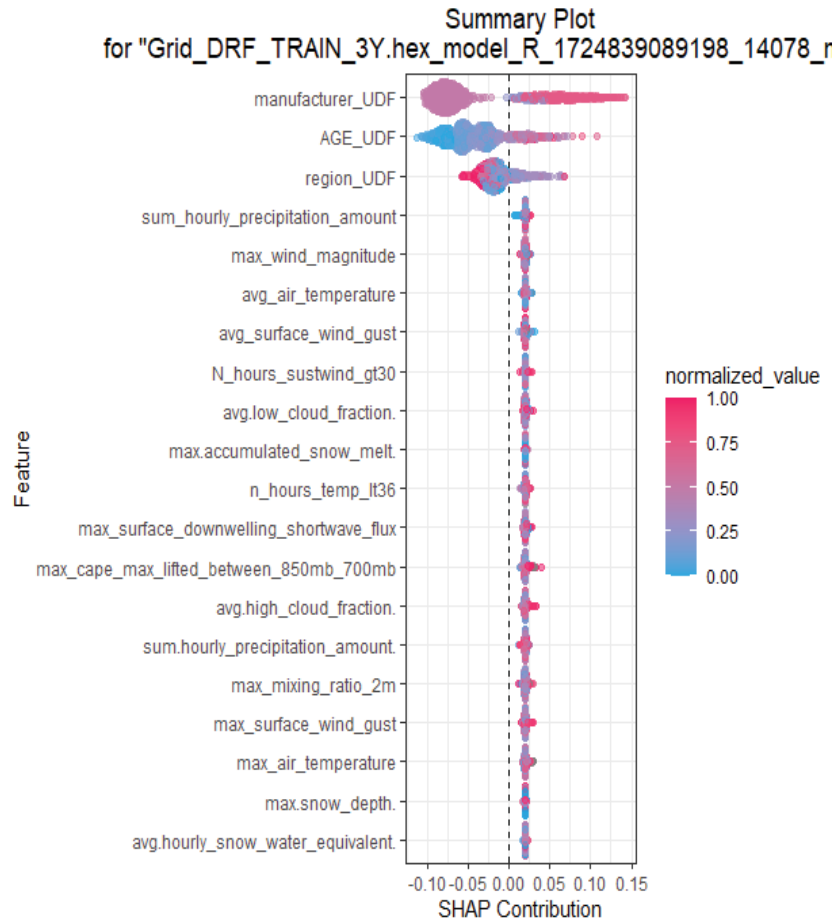


Figure 12: Variable Importance with SHAP values gives further insight into how the variables interact with the probability of failure results.

3.3 Outcome Analysis / Backtesting

The subset of historical data on which a model is trained and optimized is referred to as the in-sample data, while the subset of the dataset that has been reserved to test the model is known as the out-of-sample data. The OH & Auto Switch model uses a random sampling approach to split the dataset into Train (80%) and Test (20%) data. The results of the train data are considered in-sample backtesting and the results of the test data are considered out-of-sample backtesting.

Once the ML model is built with the training data, it is evaluated using a separate test dataset that has not yet been studied. The performance of the model is determined by the AUC value. Figure 13 shows the AUC value and ROC for the OH & Auto Switch model based on the test dataset using historical failure information between 2019-2023. The AUC value of 0.78 implies that the model possesses reasonable accuracy in terms of predicting the results.

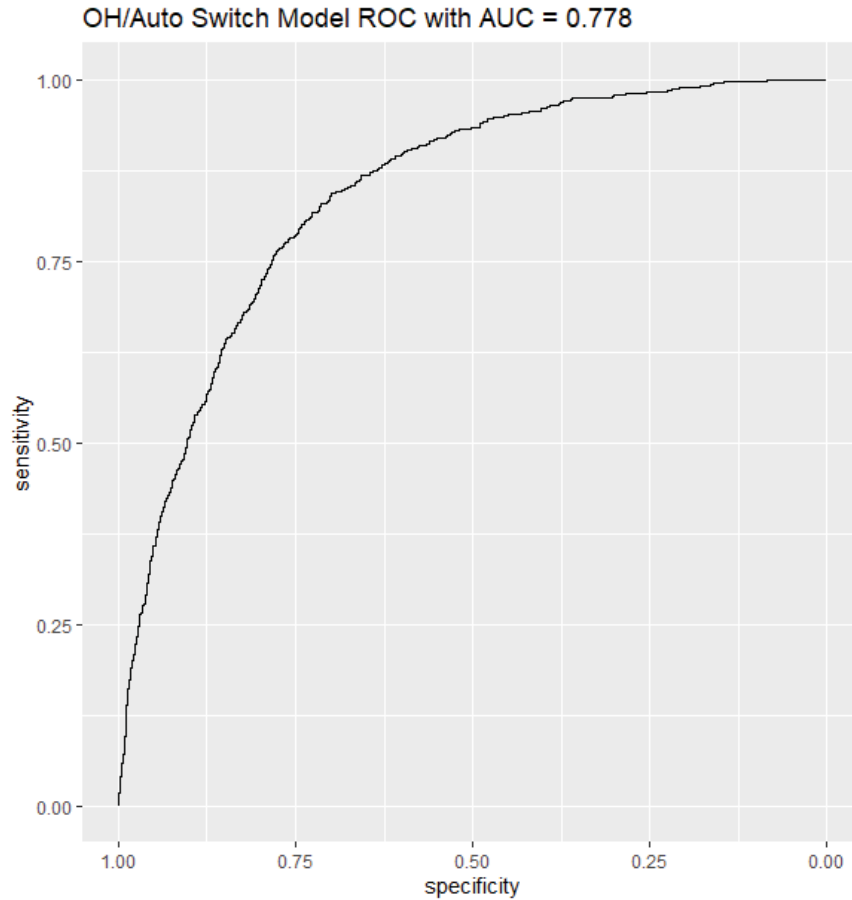


Figure 13: Out-sample backtesting result for OH & Auto Switch model based on test dataset

The impact of uncertainty in model inputs and parameters on model outputs are tested as a part of the sensitivity analysis and the results are captured in Section 3.2. In addition, the data imputations that are incorporated to address missing values before running the model are defined in Section 2.1.

3.4 Benchmarking Analysis

For the OH Switch model, different approaches like Gradient Boosting Machine (GBM) learning and Random Forest were considered during the model development phase in 2017. The analysis on these supervised ML approaches and the results are provided below.

- **Gradient Boosting Machine (GBM)** is one of the most popular forward learning ensemble methods in ML. It is a powerful technique for building predictive models for classification and regression tasks. GBM sequentially combines the predictions from various weak learner decision trees and builds a final predictive model with more accurate predictions by minimizing a defined loss function.
- **Random Forest** is a popular ML algorithm that can be used for both classification and regression problems. Random Forest is another ensemble method that combines the predictions of several decision trees to improve the predictive accuracy of the model. The individual decision trees are created based on a randomly selected subset of features at each node prior to determining the optimal split so each tree differs. The final output is determined by taking the majority vote of the

predictions from the individual decision trees. The greater number of trees in the forest generally leads to higher accuracy and prevents the problem of overfitting.

The benchmarking results of GBM shared in this section were developed using the H2O library in R on the Test data with targets based on the last 5 years of historical failure data (2019-2023). Since benchmark results were not saved during the model development phase, the benchmark models were executed in Sept 2024 for documentation purposes. Figure 14 provides the AUC values for the OH & Auto Switch model using the Random Forest and GBM methodologies.

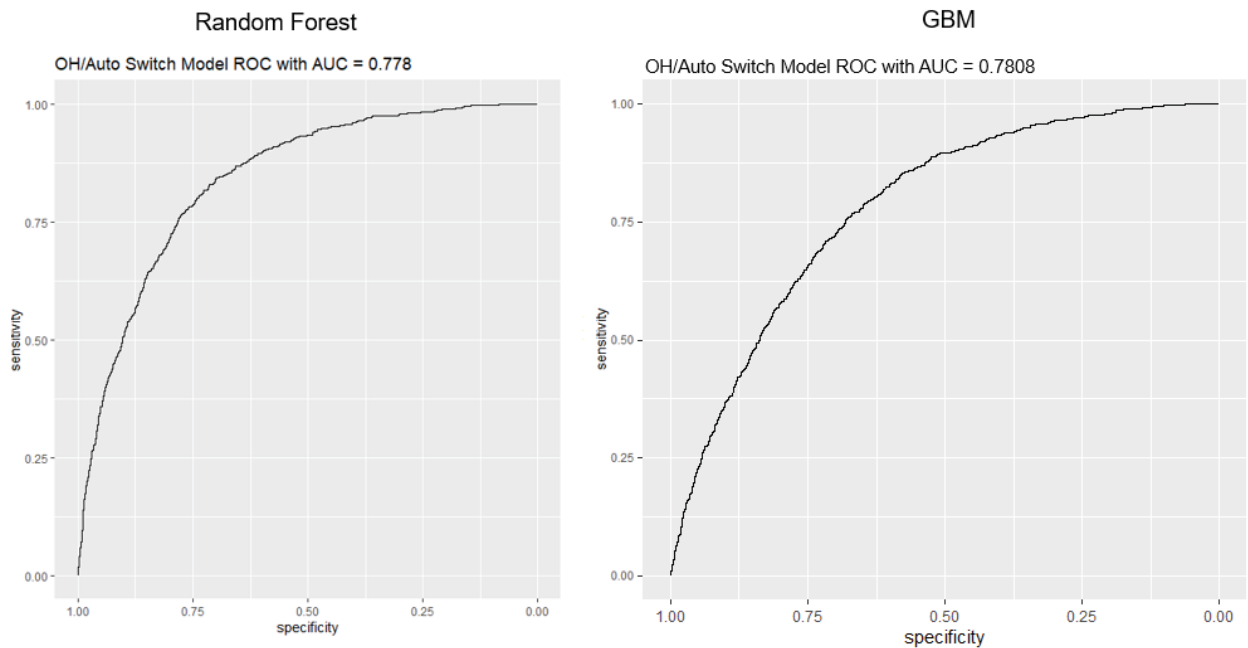


Figure 14: AUC Comparison for the OH & Auto Switch sub-model using Random Forest and GBM methodologies

For the OH & Auto Switch model in 2024, the AUC results for Random Forest and GBM were 0.7780 and 0.7808 respectively.

SCE chose Random Forest for the OH & Auto Switch model as it aligns with the modeling approach for SCE's other predictive asset failure models and achieved relatively the same AUC as GBM. SCE will continue to consider GBM as a methodology for use as part of the annual refresh of the model. Some additional advantages of using Random Forest over GBM are provided below:

- Random Forest is less sensitive to overfitting issues than GBM.
- Hyperparameter tuning is relatively easy in Random Forest when compared with GBM.

4. MODEL MANAGEMENT AND GOVERNANCE

4.1 Ongoing Monitoring Plan

Ongoing monitoring is important for ML models especially when used to make predictions or when they are run on datasets with high volatility in variable values. The OH & Auto Switch model is run manually once a year, incorporating updated input datasets to reflect the latest available data and implementing any specific model enhancements, e.g., inclusion/replacement/removal of a feature, optimization of the code, evaluation of a new performance metric, etc. During the model refresh, the limitations and assumptions of the model are also revisited by the model developers and necessary actions are taken to address them.

Performance monitoring is required only after running the model. The AUC and accuracy rate from Confusion Matrix results obtained after model refresh are compared against a threshold of 70%. If the value drops below this threshold, the reason behind the performance dip is investigated. Post-investigation, the steps required to improve the model's performance will be carried out. To monitor the model performance more thoroughly, the developers of the model plan to additionally evaluate metrics like Precision and Recall. Precision is the positive predictive value which represents the proportion of predicted failures that were predicted correctly. Recall is the true positive rate which represents the proportion of actual failures that were predicted correctly.

The model documentation and the performance results are updated once a year immediately after the model refresh.

4.2 Security and Control

The Advanced Predictive Modeling team has access to the data inputs, code, and implementation for the model. Other business units, like the Grid Hardening Strategy team, are provided access to the model outputs upon request but cannot update or modify the code.

The model is run using R programming and it can be executed in any recent versions of the R software. Current model versioning is labeled by year of refresh (e.g., 2024 refresh). The code is saved on GitHub, a platform that facilitates version control by tracking changes to the source code. Users with write or admin privileges to the repository can review proposed changes and approve them.

A contingency plan is not applicable for this model as it is an in-house model for SCE.

5. REFERENCES

RF 1: SCE's WMP 2022 Q1 Quarterly Data Report submission

<https://www.sce.com/sites/default/files/AEM/Data%20Requests/2022/SCE%20Q1%202022%20Tables%201-12.xlsx>

RF 2: Literature reference on grid search vs random search approach for hyperparameter tuning

Bergstra, J., & Bengio, Y. (2012). Random search for hyper-parameter optimization. *Journal of Machine Learning Research*, 13(1), 281-305.

RF 3: Variable Importance methodology for tree-based methods

[*Variable Importance — H2O 3.38.0.3 documentation*](#)