OrxaGrid Generation segment Case studies

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Prediction of slag formation in coal plant boilers

Challenge

The utility wanted to minimise the carbon footprint from its existing power generation assets. This is part of their sustainability strategy with a goal being 100% energy production from clean sources. Previously the utility had retrofitted their coal power plants to reduce the carbon footprint while improving/maintaining the efficiency.
Going forward, the utility wanted to explore algorithms that analyse boiler condition and predict slag formation.
In coal power plants, boilers are responsive for converting chemical energy stored in coal into thermal energy by heating water into superheated steam. Slagging on boiler furnaces (or between finance and real pass) is a specific phenomenon that results in large corrective maintenance actions. Slag build up

Solution

OrxaGrid was provided with three years of historical data at 5-minute interval from two boilers. The dataset consisted of approximately 200 boiler condition variables such as boiler furnace pressure, coal feeder, coal + primary air temperature, hot primary air control damper position at each coal mill, rotational speed, air row, overfire air, differential pressure, flue gas temperature, drum temperature, active power and so on together with failure data i.e. historical failure data.
OrxaGrid deployed feature engineering and mapped the failure data with the features. The model was built using machine learning generalised gradient boosting model with multiclassification. The model predicted slag formation between 6 to 30 days in advanced (i.e. when would the event occur) for the boilers as well as classified the slag event as medium or low event (i.e. how much or what is the severity of the event)

Result

The algorithm results were classified as True positives, false negatives and false positives:

- True positives: Slagging events that were correctly detected within the warning window i.e. 6 to 30 days in advance. This amount translated into financial savings of £320,000 per event to the utility.
- False negatives: Slagging events that happened in the boilers that were not detected within the warning window. This amount translates into repair and downtime costs.
- False positives: Slagging events that were incorrectly detected by the algorithm. This amount translates into unnecessary inspection costs.

OrxaGrid succeeded in minimising the false negatives and false positives.

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Detection of early stage failures in wind turbines

Challenge

The utility wanted to test a predictive maintenance strategy that can reduce operating costs by minimising cost of replacement and by decreasing amount of productive time lost to maintenance. The utility's goal was to foster new innovative and reliable predictive maintenance strategies backed by data.

Solution

OrxaGrid was provided with SCADA, meteorological mast, maintenance log and historical failure data of five 2MW wind turbines to build a failure prediction model. The components that were to be monitored were gearbox, generator, generator bearing, hydraulic group and transformer.
The SCADA data was given at a 10 min interval and consisted of parameters such as generator rpm, temperature in generator bearing. Temperature inside stator winding phases, rotor rpm, windspeed, wind direction, ambient temperature, active power, reactive power, transformer per phase temperature, hub controller temperature, nose cone temperature, frequency, voltages per phase and so on.
The meteorological mast signals data consisted of parameters such as wind speed (min/max/average/variance), pressure, ambient temperature, humidity, anemometer data and rain sensor data.

OrxaGrid predicted failure between 2 to 60 days before the actual failure occurred for Turbine components - gearbox, generator, generator bearing, hydraulic group and transformer.
The model was built using the features generated from the signal data, meta-mast data and log data using lag window based on the prediction time with mean and Standard Deviation and then mapping the failure data with the features. The model was built using a multi-classification machine learning model. Examples of model outputs figure 1 in appendix.

Result

The algorithm results were classified as True positives, false negatives and false positives:

- True positives: Failures of the correct wind turbine component detected within the warning window of 2 to 60 days in advance. This amount translated into financial savings to the utility as a difference between replacement and repair costs.
- False negatives: Wind turbine component failures that occurred but that were not detected within the warning window. This amount translates into replacement costs.
- False positives: Wind turbine component failures that were incorrectly detected by the algorithm i.e. when there was no failure. This amount translates into unnecessary inspection costs.

OrxaGrid succeeded in predicting transformer, generator and hydraulic group failures up to 19 days in advance, thus preventing replacement cost of £145,000 to the utility.

Scale bucket conveyor anomaly prediction

Challenge

A power plant component manufacturer reached out to OrxaGrid for redesigning their current Scale bucket Conveyor Diagnostic system monitoring approach. OrxaGrid was tasked with provided the company with a prediction model that uses real time data and forecasts equipment faults.

Solution

OrxaGrid analysed coal plant data to understand parameters that would impact the conveyor failure. A screenshot of system output is figure 2 in appendix. The technical approach is explained below.

Data acquisition: Historical data was provided in csv format. The data consisted of cut-off gate data, scale bucket conveyor data, crusher data, slag silo and historical faults and alarms. The following steps were taken:

- Pre-process the historical data
- Merge data sets of all individual data frames of operational data, Digital and analog inputs according to timestamp
- Clean data by detecting and correcting any corrupt or inaccurate records or values
- Rebuild missing data by checking Data Frame for missing or N/A values

Model building: by using a set of Independent variables and Target variable for each predefined anomaly which is referred to as "fault". Define weightage to each parameter.

- Define variables specific and directly correlated to a fault
- Identify the correlation of the independent variable with the dependent or target variable and remove correlated variables from the model
- Develop feature engineering by extending the number of independent variables.
- Check for other independent variables that can be extended along with exogenous variables
- Split the Data Frame into Train and Test samples in the ratio of 80% Train and 20% Test
- Train & Test dataset: Apply various machine learning algorithms on the Train data set with "fault" as target variable and all other variables treated as feature variables
- Fine tune algorithms parameters to get the best possible prediction accuracy (Algorithms automatically run several hundred to several thousand iterations to find the best fit the model)

Result

The algorithm model was applied to the Test data set for predicting the selected fault. The following steps were followed to evaluate the model accuracy:

- Convert probabilistic values to logical values to calculate model accuracy
- Calculate Model Accuracy: By checking how many correct fault predictions were made (True Positive) and how many predictions were missed by model (false negatives) or incorrectly predicted (False positives)

The model was provided to the company for forecasting future anomaly related events. The model predicted conveyor bucket fault with an accuracy of 92% and crusher fault at 91.3%.

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Appendix

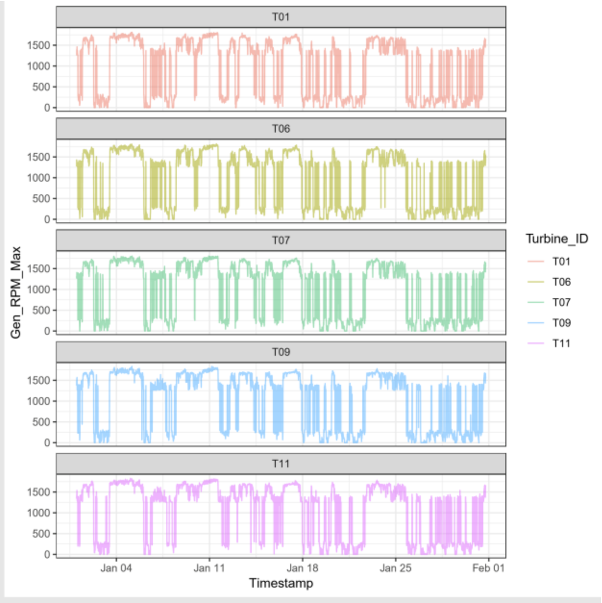

Figure 1: Wind turbine parameter evaluation

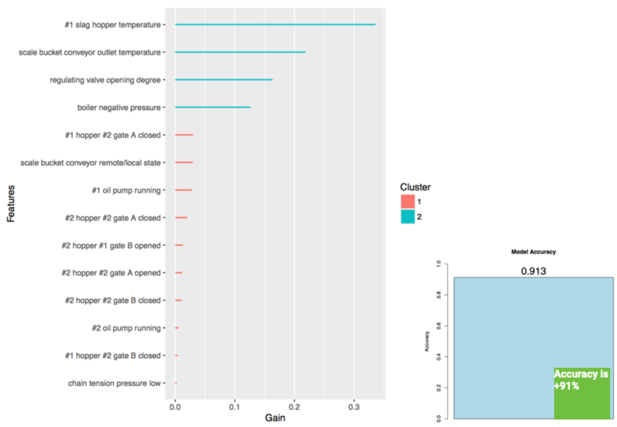

Figure 2: conveyor model evaluation