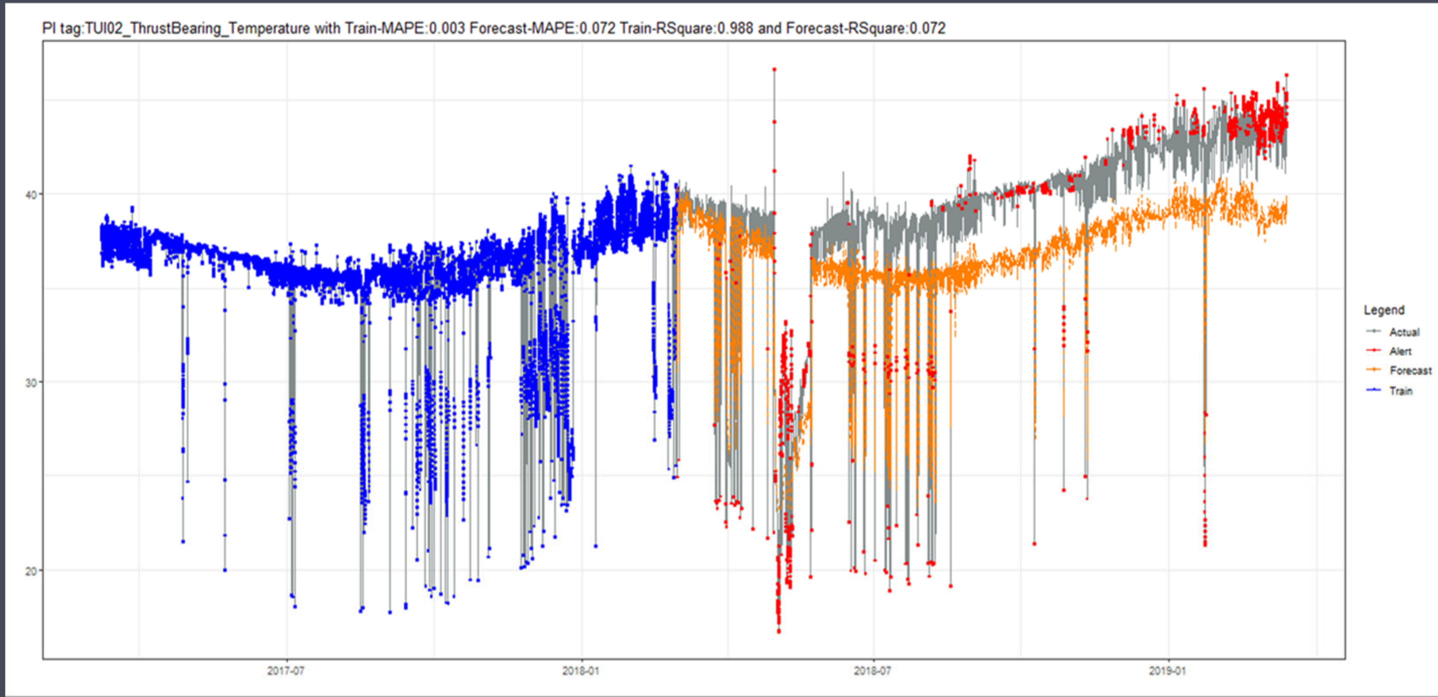
Predictive Analytics



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Asset Management Engineer

Genesis Energy

A bit about Me and an Agenda

About Me

- Currently Asset Management Engineer at Genesis Energy
- Originally a mechanical engineer, been involved in the asset management space for past six years
- Have been involved heavily on Genesis Energy asset management journey
- Currently focused on data visibility, turning our data into information and rolling out predictive analytics

Agenda

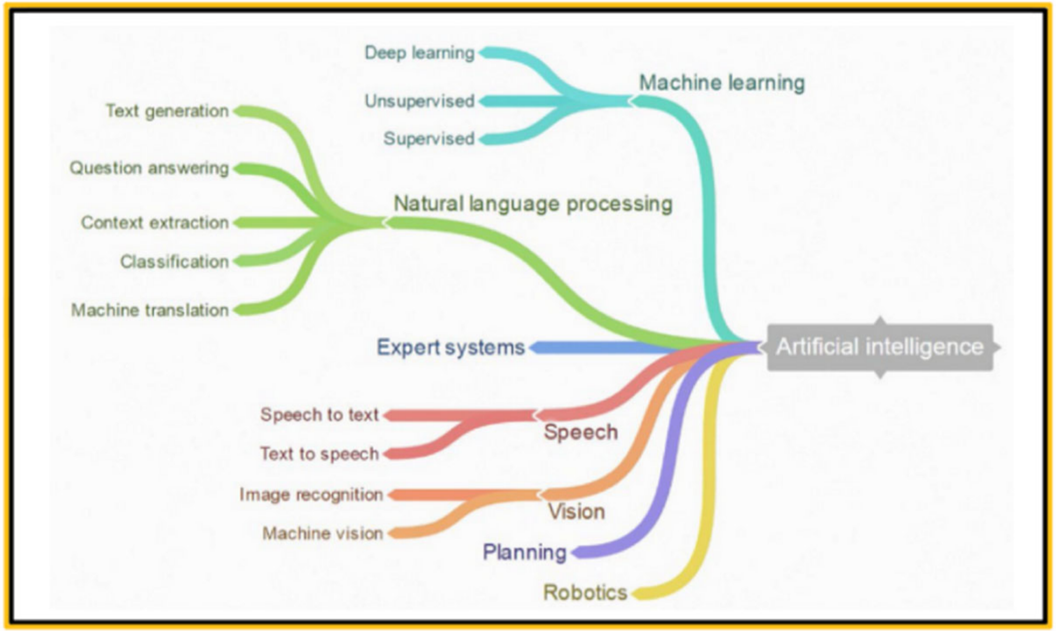
- What is Predictive Analytics, what ingredients are needed
- Our development journey
- Current state of affairs
- Examples
- What's next

Genesis Energy

- One of the ‘big five’ gentailers
- Retail side ~ 500,000 customers
    - Genesis Energy
    - Energy Online
- Generation side ~ 1600 MW
    - One thermal site (coal, gas – combined and open cycle)
    - Seven hydro stations (North and South island)
    - One wind site (plus one in development)
- Company vision to become the leader in energy management

Artificial Intelligence, Machine Learning, Predictive Analytics

- Artificial intelligence (AI) - Ability to make decisions through interpreting information
- Machine Learning – fancy name for data science. Learning from data to create a relationship/algorithm. Think y = mx + c. Is a subset of AI
- Predictive Analytics – Genesis Energy take on machine learning focused on enhancing our maintenance management



Requirements

- Data warehouse/historian – key
- Other data possibilities – CMMS, software diagnostics, market data, weather
- ‘Sandbox’/platform to model data/develop algorithms

Genesis Journey

2017 – workshop to identify what data we have and how we can be more effective with it/assist with decision making – identified the potential

2017 through 2018 – slowly developed in-house capability and platform

End of 2018 – investigated other software providers

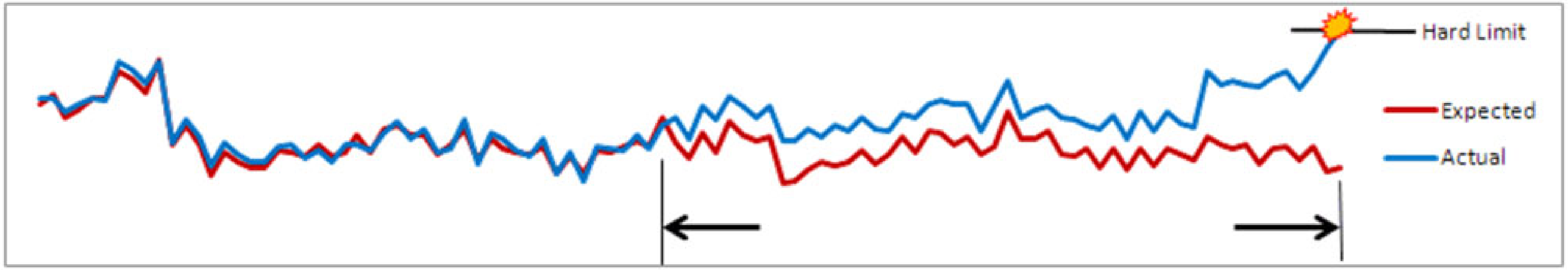
2019 – decided to commit to in-house platform and focused resource on it

What resources we've relied on

- Open source software
- Data scientists, data architects/engineers, generation engineers
- Agile workspace (average about 20% of my time for the past 24 months rather than a full time project. Has ramped up in 2019)

Predictive Analytics

— Proactively monitoring asset health to reduce cost and increase plant reliability



Benefits/Targets

Reduced Preventative Maintenance
Moving from Calendar based to Analytics triggered

Reduced Defects
Picking up on defects before they escalate.

Reduced Forced Outages
Picking up on issues before they escalate to forced outages.

It is not…

- Replacing DCS/SCADA alarming
- Real time alerting

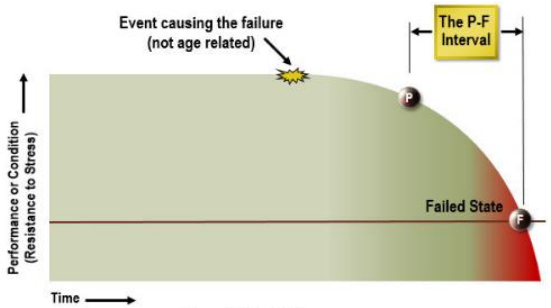
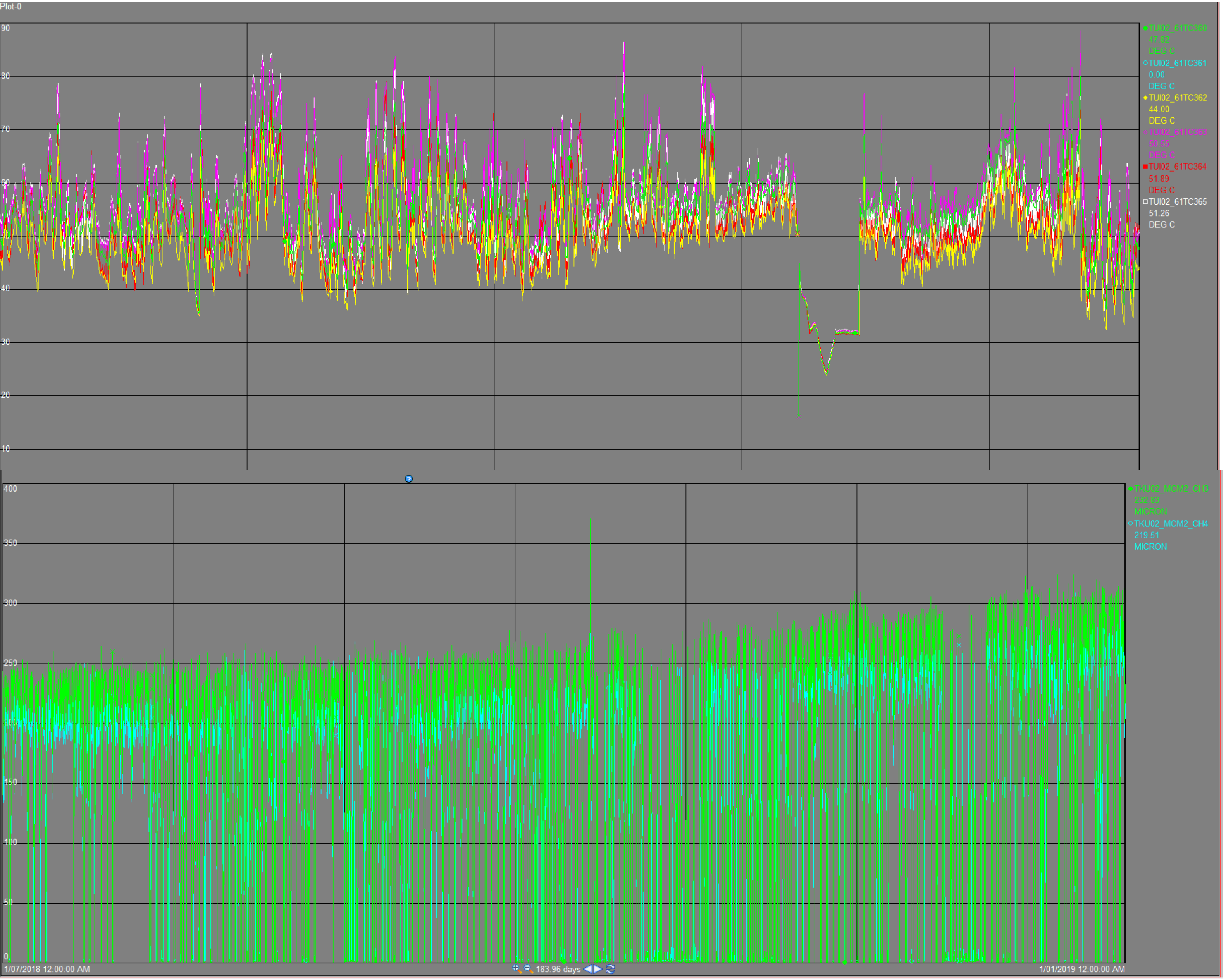


Figure1: The P-F Curve



Some typical PI screens. Both of these charts had issues identified when models were developed for them

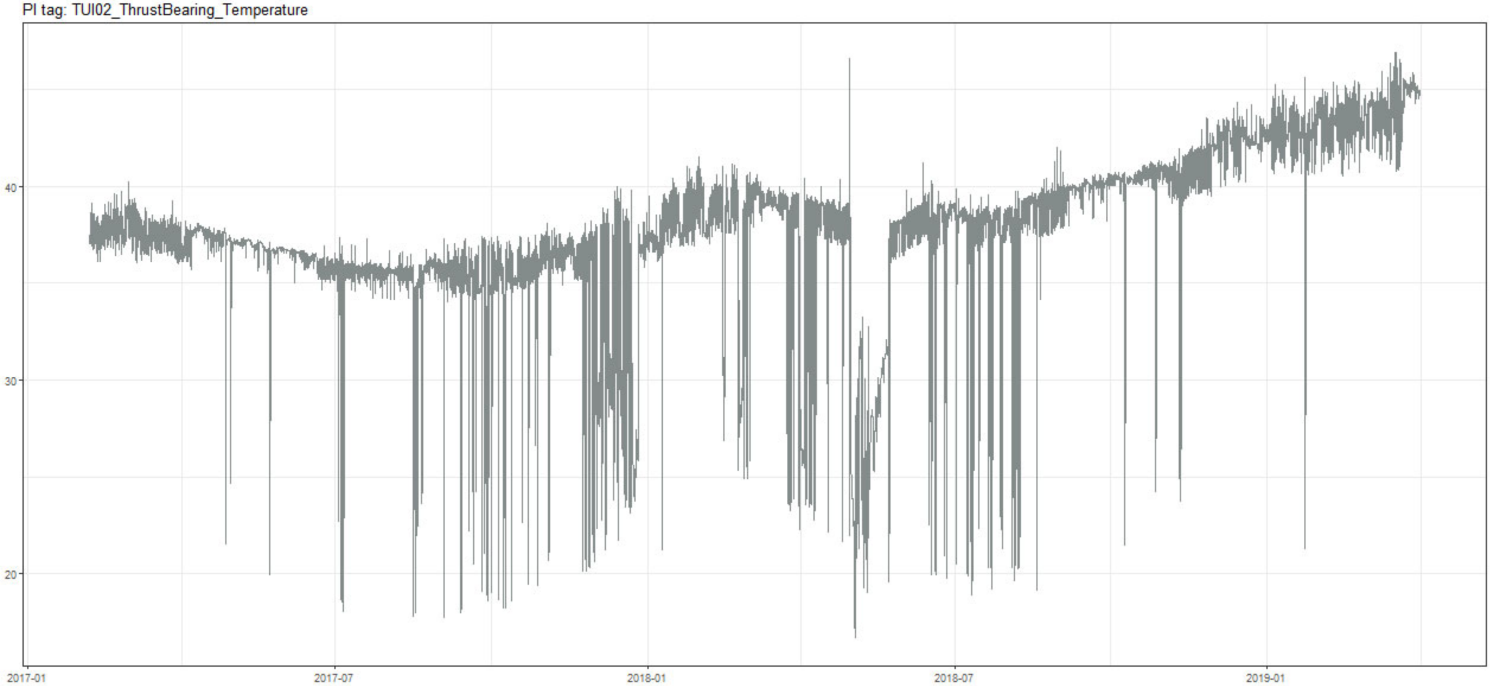
Our In-house Tool

Formula

TUI02_ThrustBearing_Temperature ~ TUI02_Unit_MW + TUI02_TurbineBearing_Temperature + TUI02_GeneratorBearing_Temperature + KTW_CoolingWater_Temperature_24HourAverage

Train | Delete | Reset | Zoom-in | Zoom-out | Import-remove | Save

PI tag: TUI02_ThrustBearing_Temperature



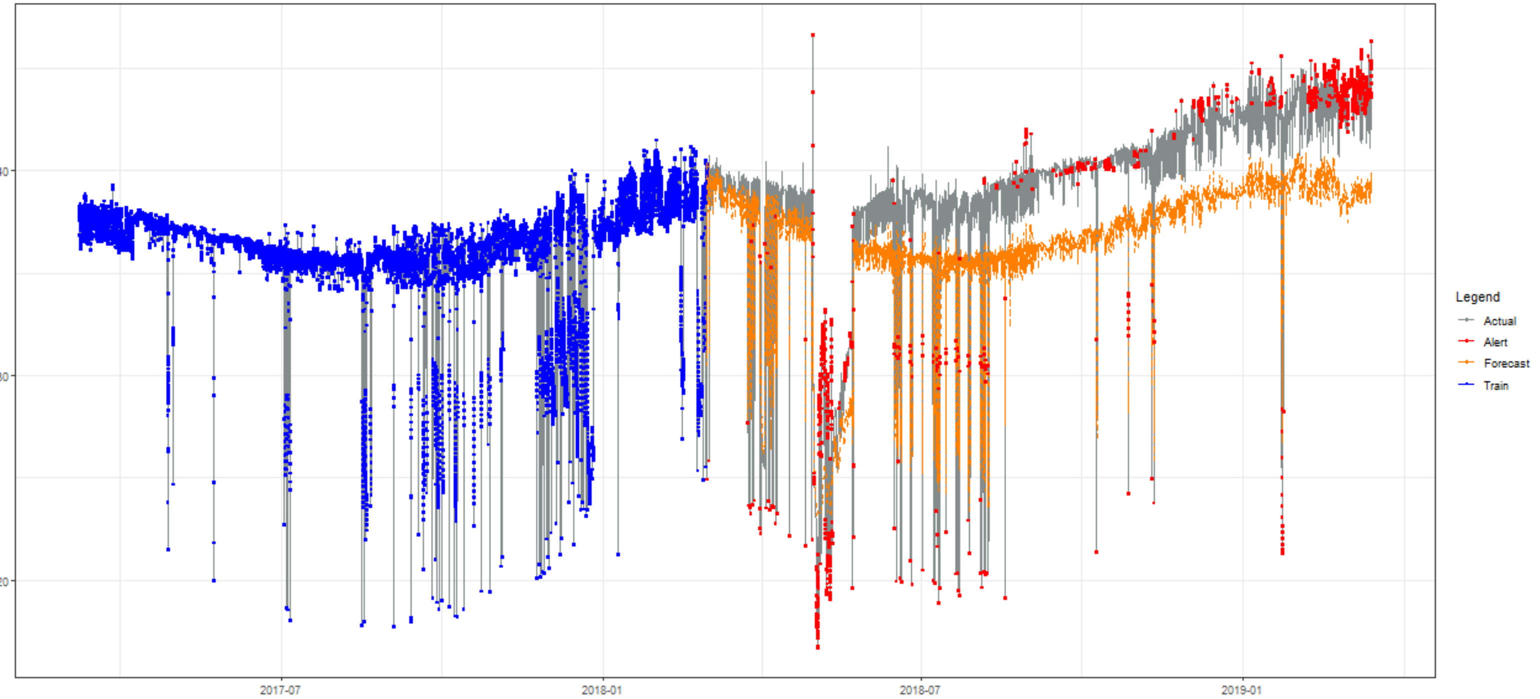
Ability to select input variables, remove unrelated data (eg plant in outage), training periods and forecasting check to validate model

Thrust Bearing Temperature

TUI02_ThrustBearing_Temperature ~ TUI02_Unit_MW + TUI02_TurbineBearing_Temperature + TUI02_GeneratorBearing_Temperature + TUI_PowerStation_Temperature24HourMovingAverage

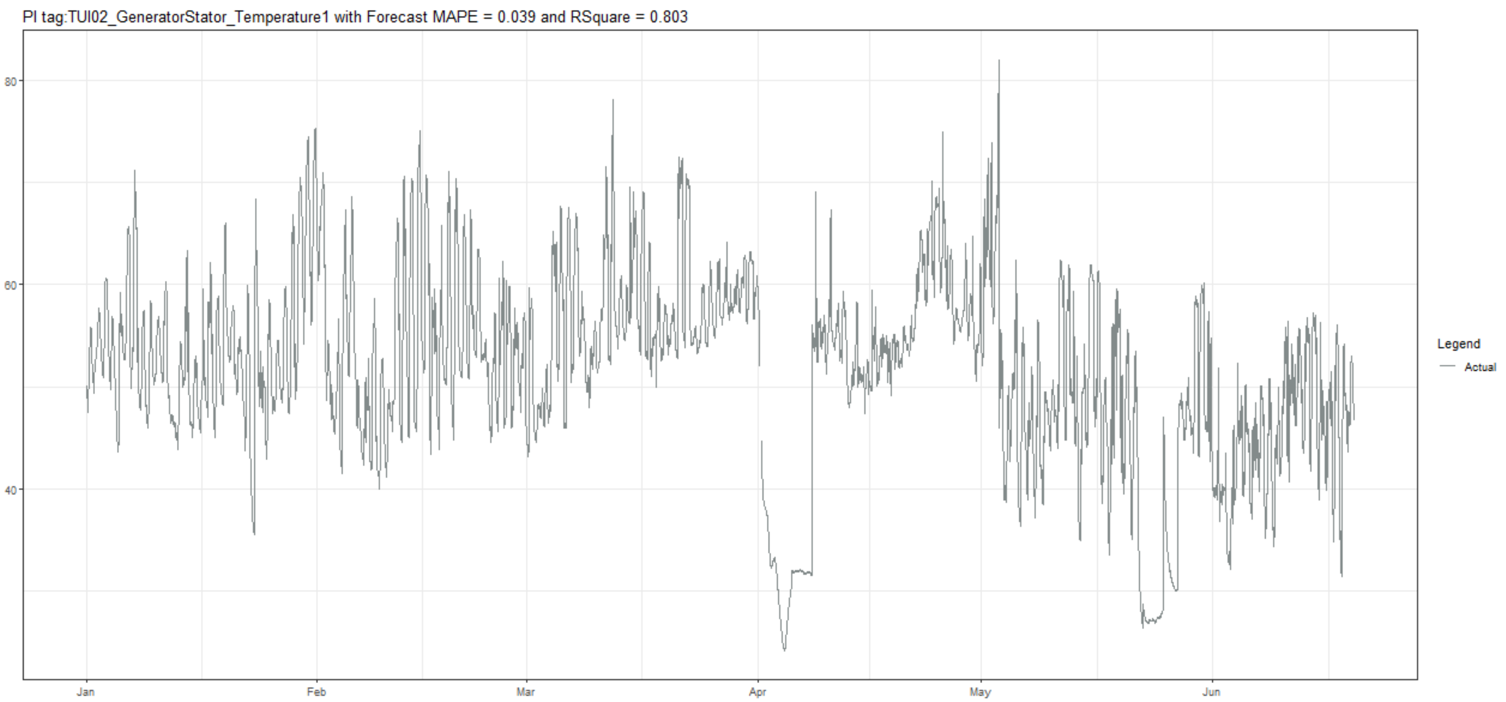
Train | Delete | Reset | Zoom-in | Zoom-out | Import-remove | Save

PI tag:TUI02_ThrustBearing_Temperature with Train-MAPE:0.003 Forecast-MAPE:0.072 Train-RSquare:0.988 and Forecast-RSquare:0.072



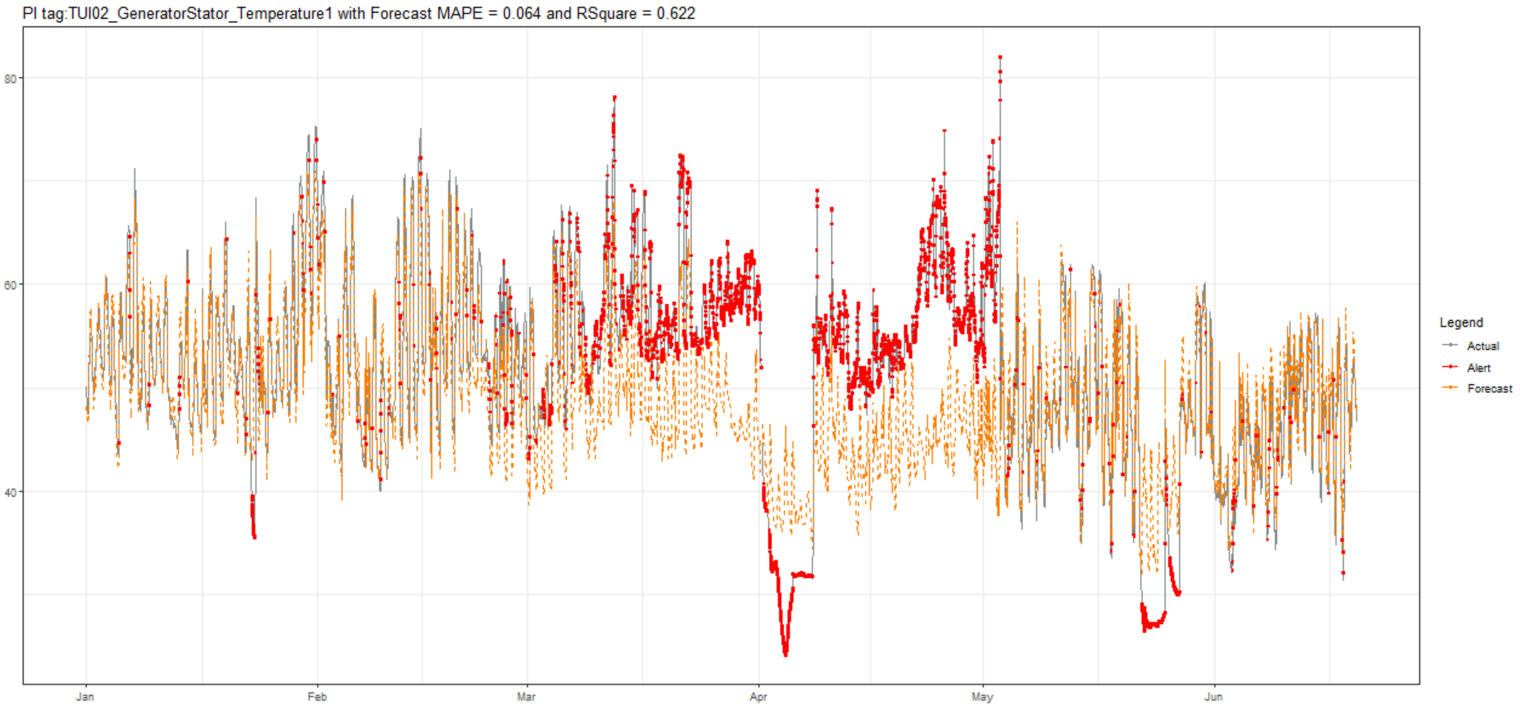
This shows an example of a training period (blue), forecasted period (orange), actual sensor data (grey) and alerting (red highlights)

Generator Stator Temperature - Actual



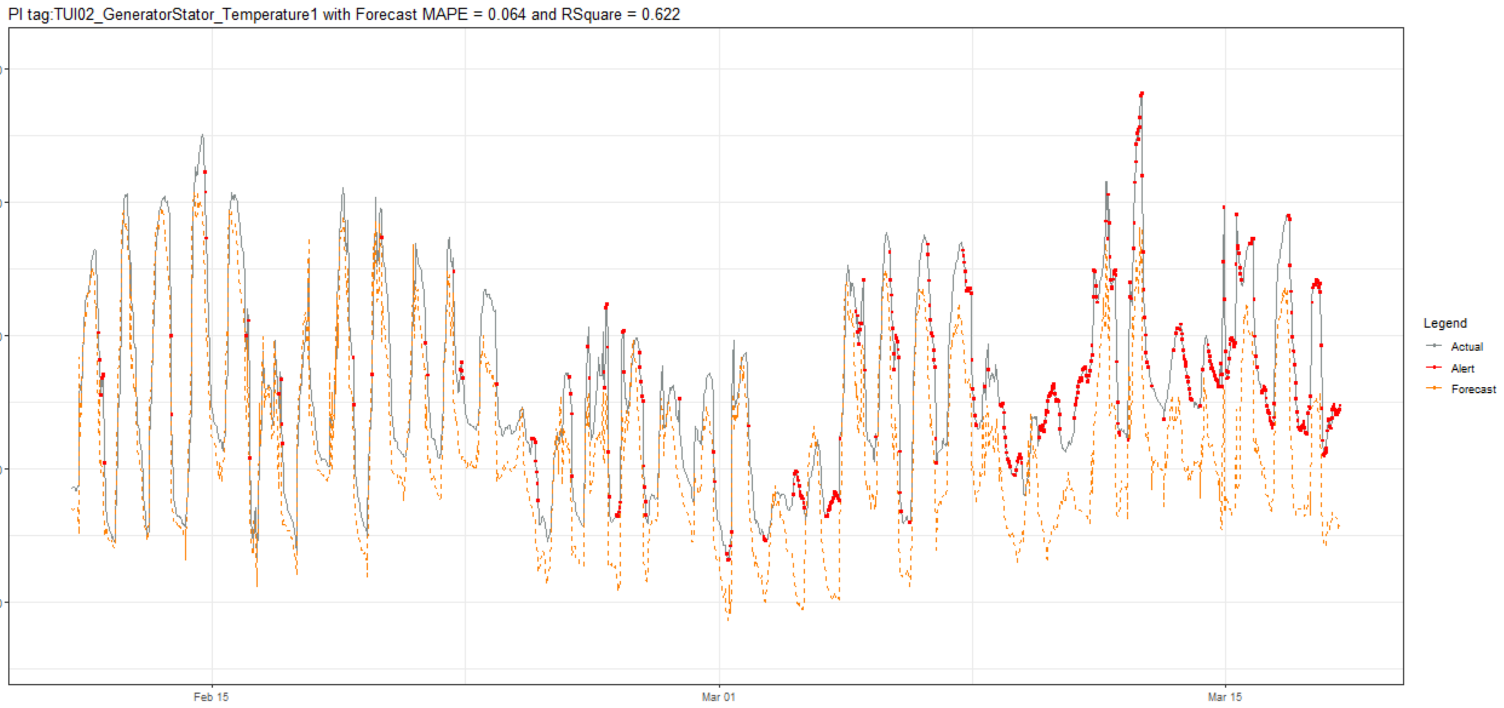
This example looks at the stator temperature at one of the power stations

Generator Stator Temperature – With Model



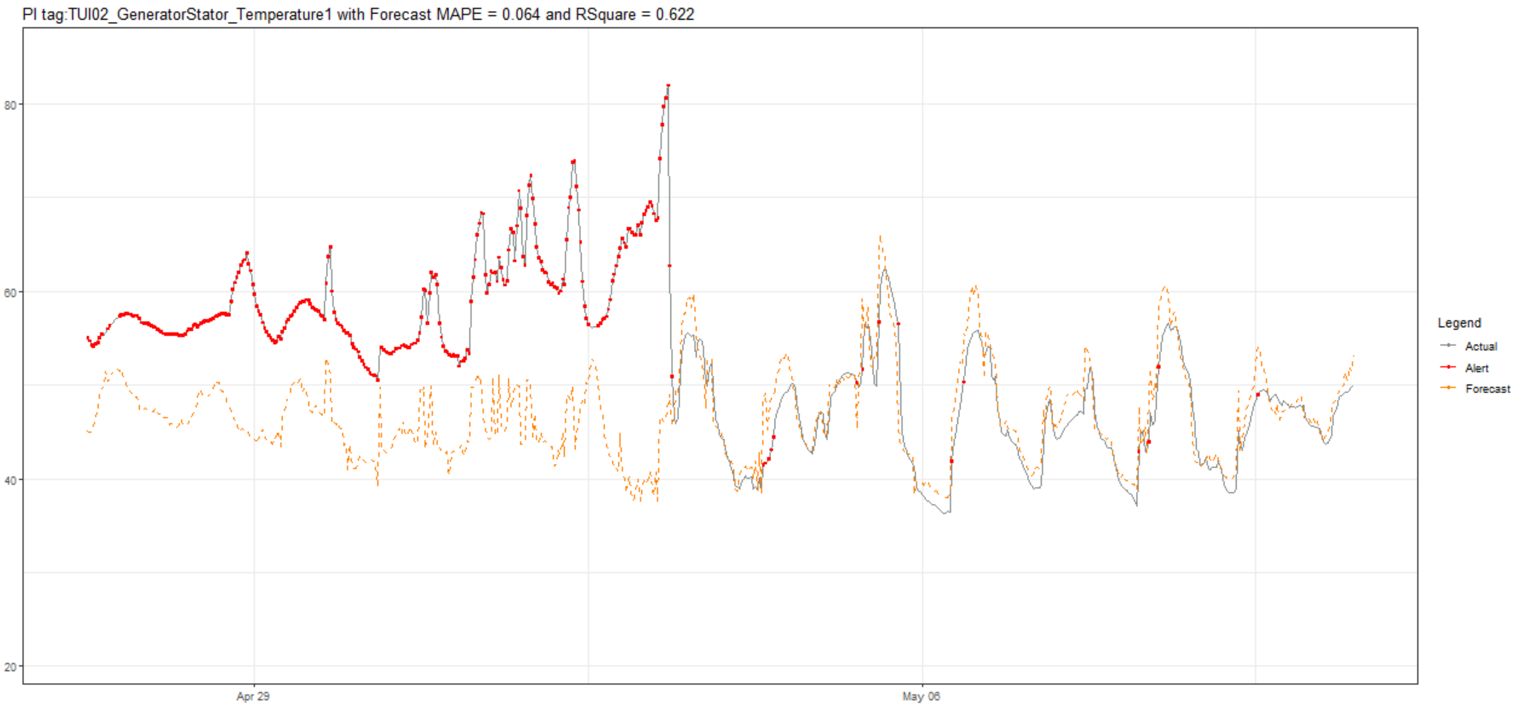
Here is the model overlaid on the actual data. You can see there's a period where the model is in alert when the actual temperature was higher than predicted

Generator Stator Temperature – With Model



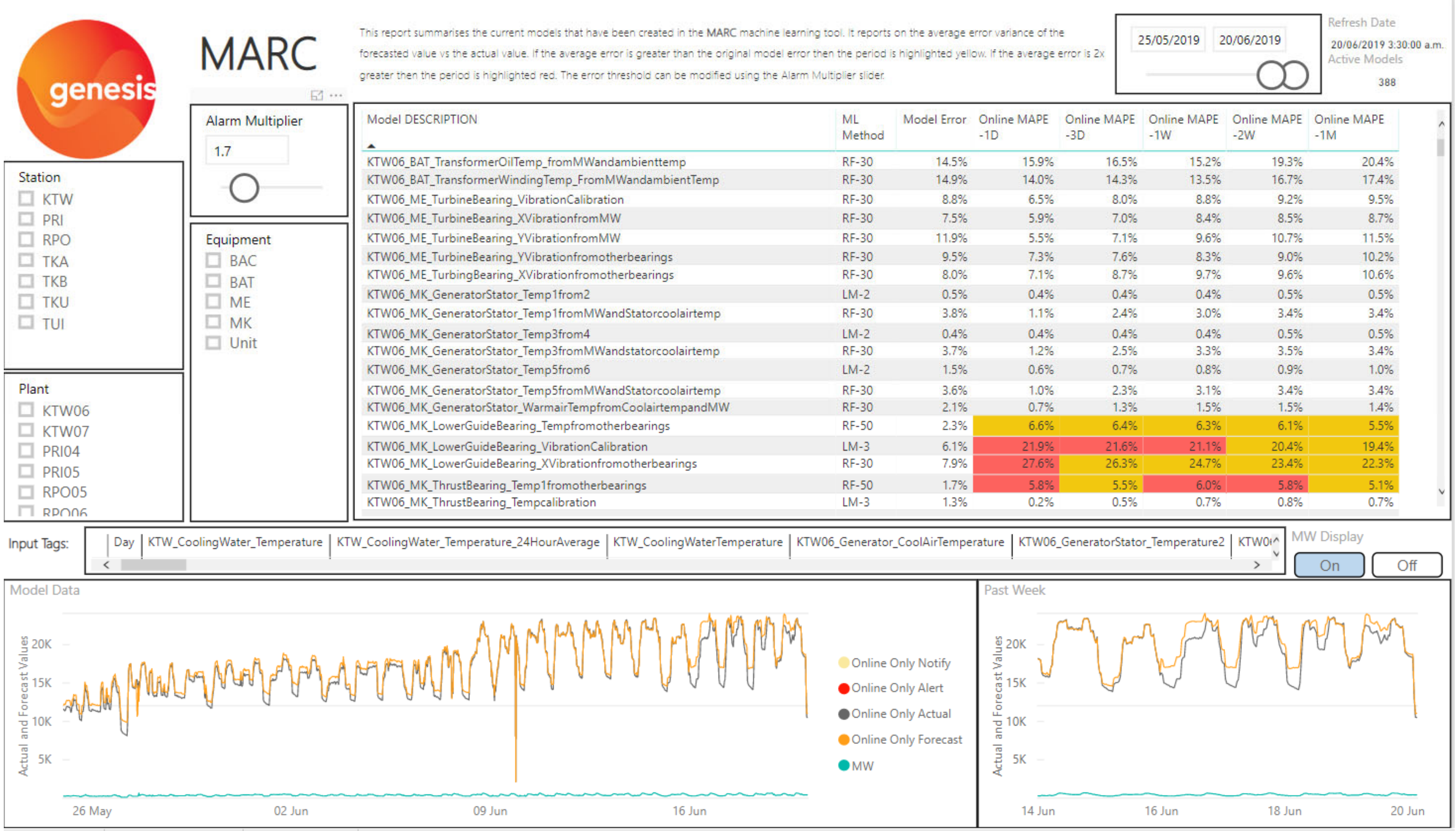
This is the start of the divergence of the actual temperature to the model. The both start out in sync then the actual temperature starts to rise

Generator Stator Temperature – With Model



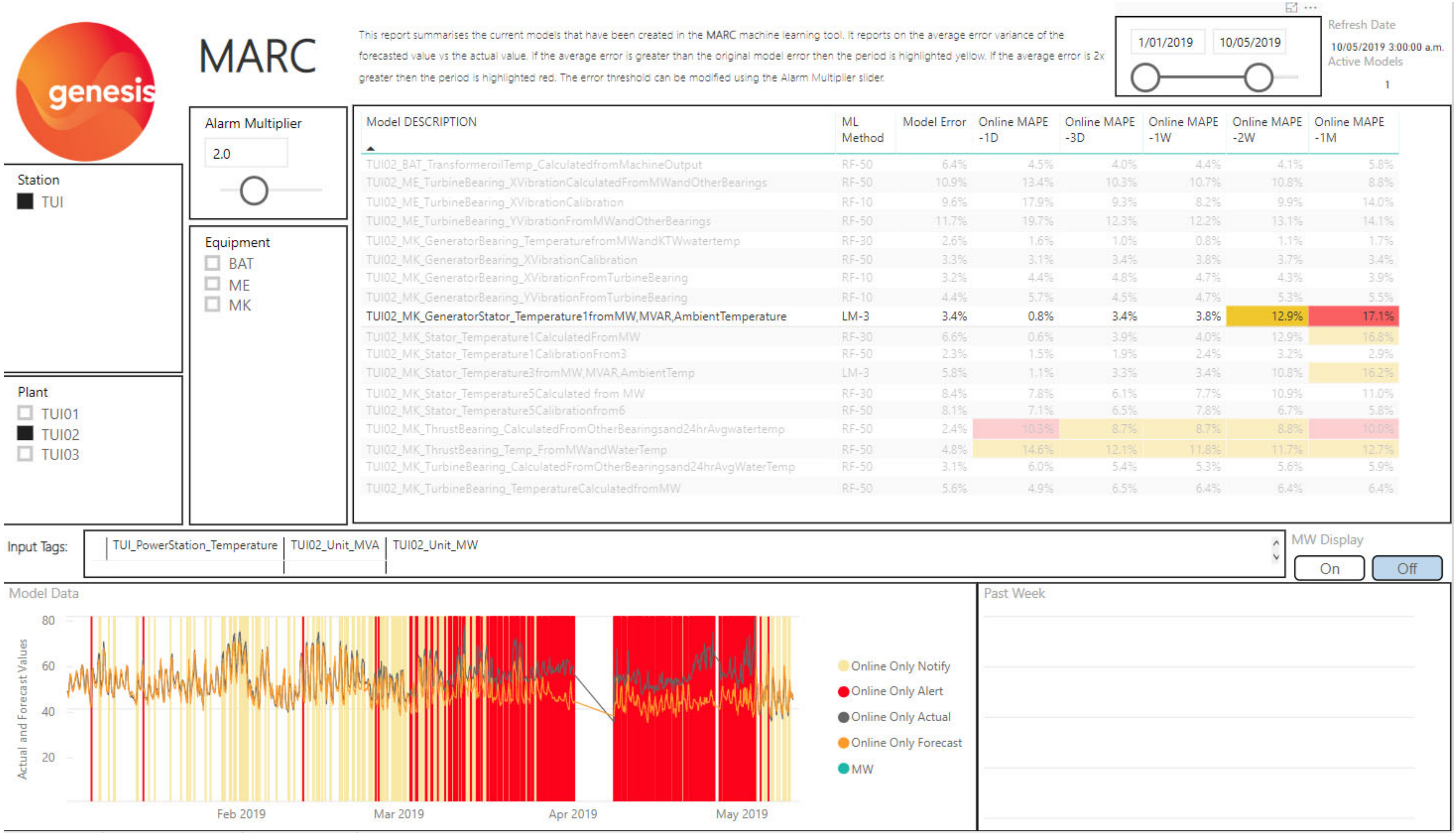
Here the issue was resolved. There was a particularly blocked air filter which meant cooling was limited. Post repair you can see the model and actual match well again

How to Manage Multiple Models – Power BI



Model DESCRIPTION	ML Method	Model Error	Online MAPE -1D	Online MAPE -3D	Online MAPE -1W	Online MAPE -2W	Online MAPE -1M
KTW06_BAT_TransformerOilTemp_fromMWandambienttemp	RF-30	14.5%	15.9%	16.5%	15.2%	19.3%	20.4%
KTW06_BAT_TransformerWindingTemp_FromMWandambientTemp	RF-30	14.9%	14.0%	14.3%	13.5%	16.7%	17.4%
KTW06_ME_TurbineBearing_VibrationCalibration	RF-30	8.8%	6.5%	8.0%	8.8%	9.2%	9.5%
KTW06_ME_TurbineBearing_XVibrationfromMW	RF-30	7.5%	5.9%	7.0%	8.4%	8.5%	8.7%
KTW06_ME_TurbineBearing_YVibrationfromMW	RF-30	11.9%	5.5%	7.1%	9.6%	10.7%	11.5%
KTW06_ME_TurbineBearing_YVibrationfromotherbearings	RF-30	9.5%	7.3%	7.6%	8.3%	9.0%	10.2%
KTW06_ME_TurbingBearing_XVibrationfromotherbearings	RF-30	8.0%	7.1%	8.7%	9.7%	9.6%	10.6%
KTW06_MK_GeneratorStator_Temp1from2	LM-2	0.5%	0.4%	0.4%	0.4%	0.5%	0.5%
KTW06_MK_GeneratorStator_Temp1fromMWandStatorcoolairtemp	RF-30	3.8%	1.1%	2.4%	3.0%	3.4%	3.4%
KTW06_MK_GeneratorStator_Temp3from4	LM-2	0.4%	0.4%	0.4%	0.4%	0.5%	0.5%
KTW06_MK_GeneratorStator_Temp3fromMWandstatorcoolairtemp	RF-30	3.7%	1.2%	2.5%	3.3%	3.5%	3.4%
KTW06_MK_GeneratorStator_Temp5from6	LM-2	1.5%	0.6%	0.7%	0.8%	0.9%	1.0%
KTW06_MK_GeneratorStator_Temp5fromMWandStatorcoolairtemp	RF-30	3.6%	1.0%	2.3%	3.1%	3.4%	3.4%
KTW06_MK_GeneratorStator_WarmairTempfromCoolairtempandMW	RF-30	2.1%	0.7%	1.3%	1.5%	1.5%	1.4%
KTW06_MK_LowerGuideBearing_Tempfromotherbearings	RF-50	2.3%	6.6%	6.4%	6.3%	6.1%	5.5%
KTW06_MK_LowerGuideBearing_VibrationCalibration	LM-3	6.1%	21.9%	21.6%	21.1%	20.4%	19.4%
KTW06_MK_LowerGuideBearing_XVibrationfromotherbearings	RF-30	7.9%	27.6%	26.3%	24.7%	23.4%	22.3%
KTW06_MK_ThrustBearing_Temp1fromotherbearings	RF-50	1.7%	5.8%	5.5%	6.0%	5.8%	5.1%
KTW06_MK_ThrustBearing_Tempcalibration	LM-3	1.3%	0.2%	0.5%	0.7%	0.8%	0.7%

Generator temperature example from before



Model DESCRIPTION	ML Method	Model Error	Online MAPE -1D	Online MAPE -3D	Online MAPE -1W	Online MAPE -2W	Online MAPE -1M
TUI02_BAT_TransformeroilTemp_CalculatedfromMachineOutput	RF-50	6.4%	4.5%	4.0%	4.4%	4.1%	5.8%
TUI02_ME_TurbineBearing_XVibrationCalculatedFromMWandOtherBearings	RF-50	10.9%	13.4%	10.3%	10.7%	10.8%	8.8%
TUI02_ME_TurbineBearing_XVibrationCalibration	RF-10	9.6%	17.9%	9.3%	8.2%	9.9%	14.0%
TUI02_ME_TurbineBearing_YVibrationFromMWandOtherBearings	RF-50	11.7%	19.7%	12.3%	12.2%	13.1%	14.1%
TUI02_MK_GeneratorBearing_TemperaturefromMWandKTWwatertemp	RF-30	2.6%	1.6%	1.0%	0.8%	1.1%	1.7%
TUI02_MK_GeneratorBearing_XVibrationCalibration	RF-50	3.3%	3.1%	3.4%	3.8%	3.7%	3.4%
TUI02_MK_GeneratorBearing_XVibrationFromTurbineBearing	RF-10	3.2%	4.4%	4.8%	4.7%	4.3%	3.9%
TUI02_MK_GeneratorBearing_YVibrationFromTurbineBearing	RF-10	4.4%	5.7%	4.5%	4.7%	5.3%	5.5%
TUI02_MK_GeneratorStator_Temperature1fromMW,MVAR,AmbientTemperature	LM-3	3.4%	0.8%	3.4%	3.8%	12.9%	17.1%
TUI02_MK_Stator_Temperature1CalculatedFromMW	RF-30	6.6%	0.6%	3.9%	4.0%	12.9%	16.8%
TUI02_MK_Stator_Temperature1CalibrationFrom3	RF-50	2.3%	1.5%	1.9%	2.4%	3.2%	2.9%
TUI02_MK_Stator_Temperature3fromMW,MVAR,AmbientTemp	LM-3	5.8%	1.1%	3.3%	3.4%	10.8%	16.2%
TUI02_MK_Stator_Temperature5Calculated from MW	RF-30	8.4%	7.8%	6.1%	7.7%	10.9%	11.0%
TUI02_MK_Stator_Temperature5Calibrationfrom6	RF-50	8.1%	7.1%	6.5%	7.8%	6.7%	5.8%
TUI02_MK_ThrustBearing_CalculatedFromOtherBearingsand24hrAvgwatertemp	RF-50	2.4%	10.3%	8.7%	8.7%	8.8%	10.0%
TUI02_MK_ThrustBearing_Temp_FromMWandWaterTemp	RF-50	4.8%	14.6%	12.1%	11.8%	11.7%	12.7%
TUI02_MK_TurbineBearing_CalculatedFromOtherBearingsand24hrAvgWaterTemp	RF-50	3.1%	6.0%	5.4%	5.3%	5.6%	5.9%
TUI02_MK_TurbineBearing_TemperatureCalculatedfromMW	RF-50	5.6%	4.9%	6.5%	6.4%	6.4%	6.4%

Achievements so far

- Since March built 400+ models
- This has been developed with 50% FTE and predominately internal resource costs
- 10 validated asset health deteriorations/performance monitoring
- Good engineering buy in for ones that have been involved with an issue
- Have a large backlog of potential models still to create

Going Forward

- Proven in-house platform is viable and working for us
- Aiming for 1000 models in year 1 based on most critical assets, historical failures and current work stream of maintenance reviews
- Building the business process on how to manage Model 'alerts' and cultural engagement
    - Site tours to operations crew to keep them up to date
    - How to engage with engineering vs operations vs what they might already know
    - Confidence that modelling can replace time based maintenance
- Install more sensors to capture data and fill current data/modelling gaps

Thankyou

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