PI World 2020 Lab

Usage-based, Condition-based and Predictive Maintenance using the PI System

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Usage-based, Condition-based and Predictive Maintenance using the PI System

Hands-on Lab – OSIsoft PI World 2020

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Usage-based, Condition-based and Predictive Maintenance using the PI System

Lab Description

In this lab, we walk through scenarios to illustrate ***the use of process data and machine condition data and a layered approach to maintenance via usage-based, condition-based and predictive maintenance.***

Data sources include traditional plant instrumentation such as PLCs and SCADA, the newer IoT devices, and from machine condition monitoring such as vibration, oil analysis etc.

Usage-based maintenance includes utilizing operational metrics such as motor run-hours, compressor starts/stops, grinder tonnage etc. And, condition-based maintenance utilizes measurements such as filter deltaP, bearing temperature, valve stroke travel, and others. Predictive maintenance can be using simple analytics such as monitoring vibration (rms, peak etc.) to predict RUL (remaining useful life), heat-exchanger fouling to schedule cleaning, etc.

In this lab will also discuss predictive maintenance use cases that require advanced analytics, including machine learning, such as APR (advanced pattern recognition), anomaly detection, and others.

Who should attend? Experienced PI user

Duration: 3 hours

Summary

Condition-based maintenance (CBM) is a strategy where you monitor the actual condition of an asset to decide what maintenance needs to be done – see wiki for a broader definition. This contrasts with a break-fix strategy (reactive or corrective maintenance), and calendar scheduled maintenance (clean and lube every 3 months, laser align every 6 months etc.) regardless of the condition of the asset and whether it was used or not.

Increasing equipment uptime means preventing failures before they happen; and in turn, this requires you to have a list of likely failures and the appropriate measurements and relevant condition monitoring for the process and equipment/component.

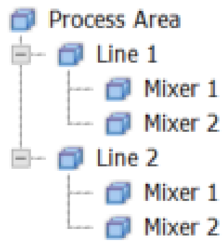
This lab's objective is to walk-through the use of equipment and process data for a *<u>layered approach</u>* to uptime and reliability via usage based, condition-based and predictive – simple and advanced (machine learning) - maintenance.

- Exercise 1: Usage base maintenance – motor run-hours and valve actuation counts
- Exercise 2: Condition-based maintenance – bearing temperature high alert
- Exercise 3a: Predictive maintenance (simple) – univariate (single variable) – increasing bearing vibration trend extrapolated to predict time to maintenance
- Exercise 3b: CM, PM and PdM - Using engine failure history to support the decision criteria and quantify the benefits for moving from corrective maintenance (CM) to preventive maintenance (PM) to predictive maintenance (PdM)
- Exercise 4: Asset health score – utilize multiple condition assessment rules with appropriate weighting factors to process/equipment indicators to calculate an overall asset health score

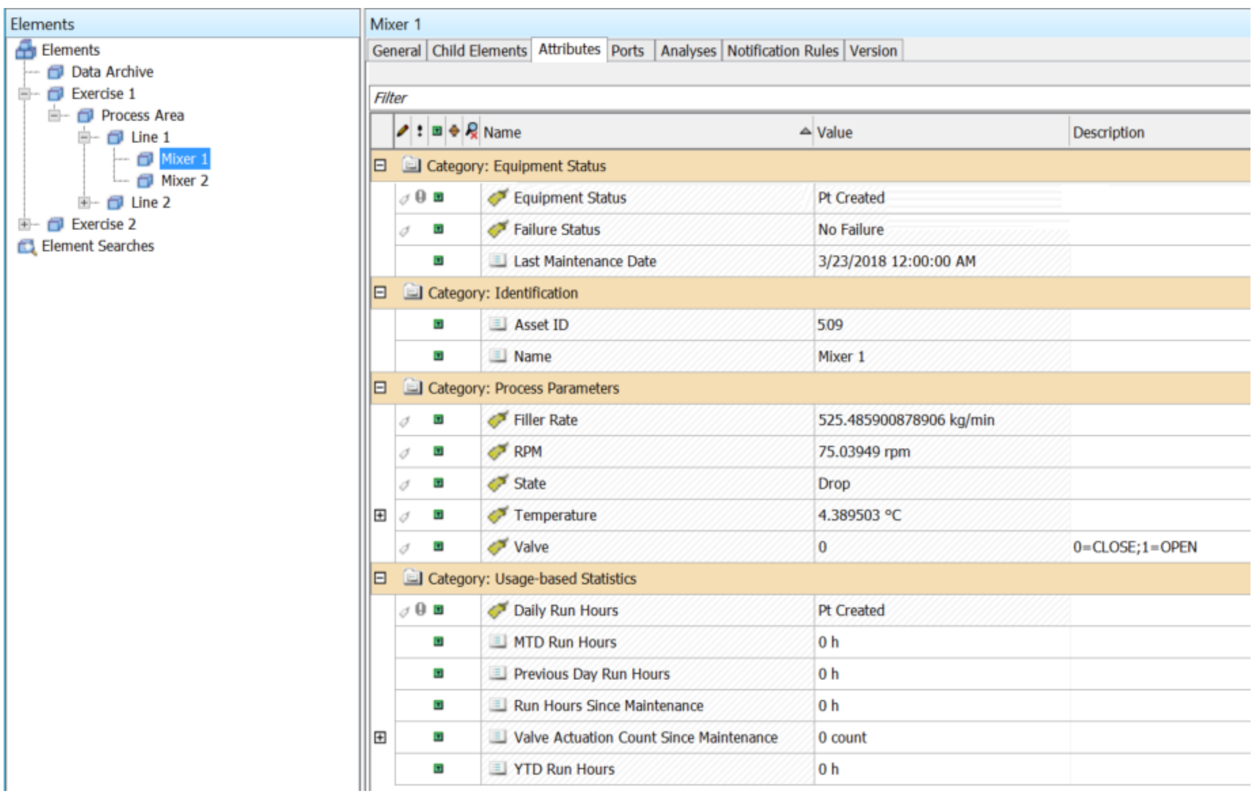
Exercise 1: Usage-based Maintenance

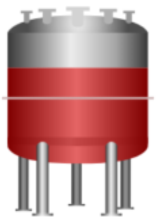
In this exercise, motor run-hours and valve actuation counts are calculated to serve as a basis for usage-based maintenance.

We use an ice-cream factory running two process lines – Line 1 and Line 2, with two mixers on each line.



The hands-on portion includes building the run-hours calculations in AF, and the relevant PI Vision displays as shown below.

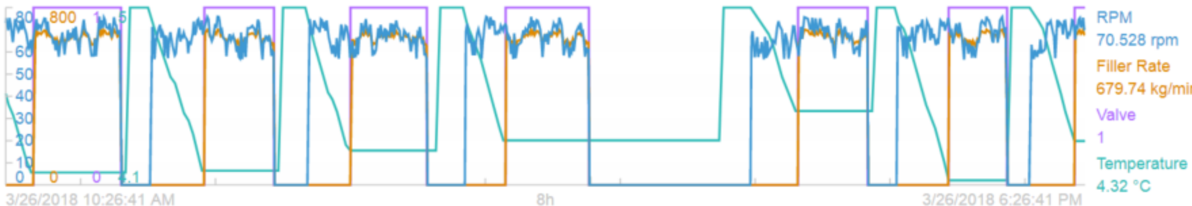


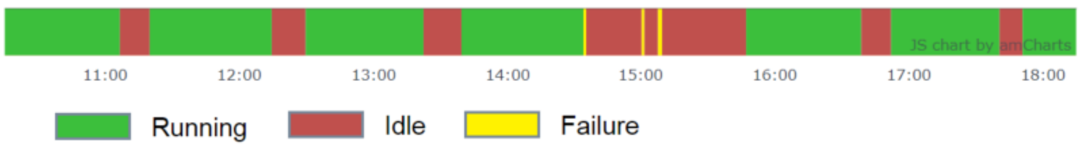


Mixer 1

509

Name	Value
Mixer 1|Last Maintenance Date	3/26/2018 12:00:00 AM
Mixer 1|MTD Run Hours	55.643
Mixer 1|Previous Day Run Hours	16.244
Mixer 1|Run Hours Since Maintenance	14.827
Mixer 1|Valve Actuation Count Since Maintenance	16
Mixer 1|YTD Run Hours	55.643





Name	Value	Units
Mixer 1|Last Maintenance Date	3/26/2018 12:00:00 AM	
Mixer 1|MTD Run Hours	55.143	h
Mixer 1|Previous Day Run Hours	16.244	h
Mixer 1|Run Hours Since Maintenanc	14.327	h
Mixer 1|Valve Actuation Count Since	16	count

Name	Value	Units
Mixer 1|Last Maintenance Date	3/23/2018 12:00:00 AM	
Mixer 1|MTD Run Hours	7.5494	h
Mixer 1|Previous Day Run Hours	0	h
Mixer 1|Run Hours Since Maintenanc	7.5494	h
Mixer 1|Valve Actuation Count Since	62	count

Name	Value	Units
Mixer 2|Last Maintenance Date	3/25/2018 12:00:00 AM	
Mixer 2|MTD Run Hours	55.889	h
Mixer 2|Previous Day Run Hours	16.317	h
Mixer 2|Run Hours Since Maintenanc	30.733	h
Mixer 2|Valve Actuation Count Since	34	count

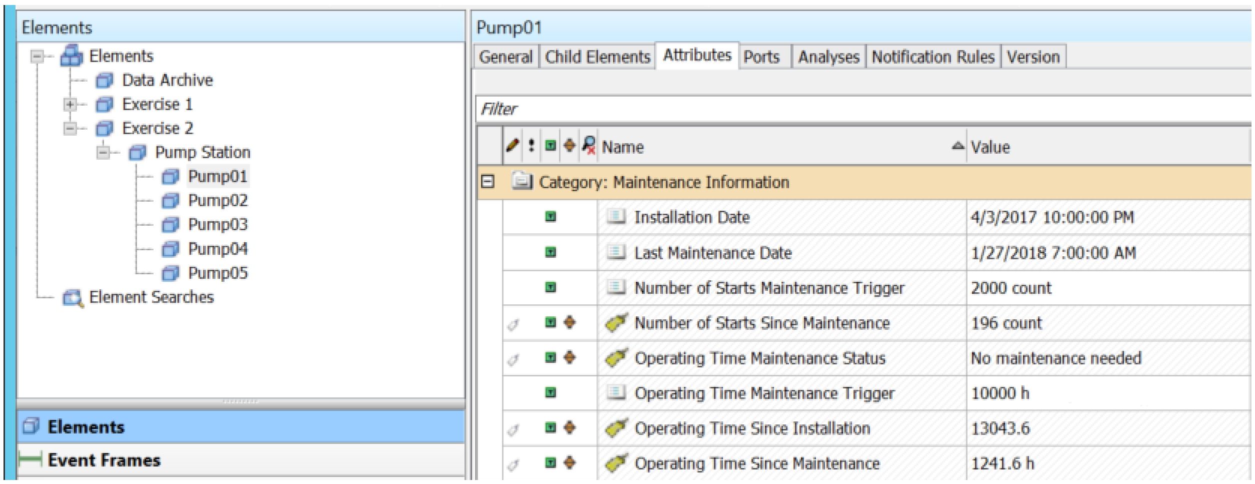
Name	Value	Units
Mixer 2|Last Maintenance Date	3/24/2018 12:00:00 AM	
Mixer 2|MTD Run Hours	7.4606	h
Mixer 2|Previous Day Run Hours	0	h
Mixer 2|Run Hours Since Maintenanc	7.4606	h
Mixer 2|Valve Actuation Count Since	53	count

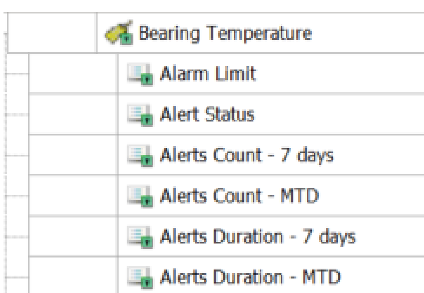
Exercise 2: Condition-based maintenance

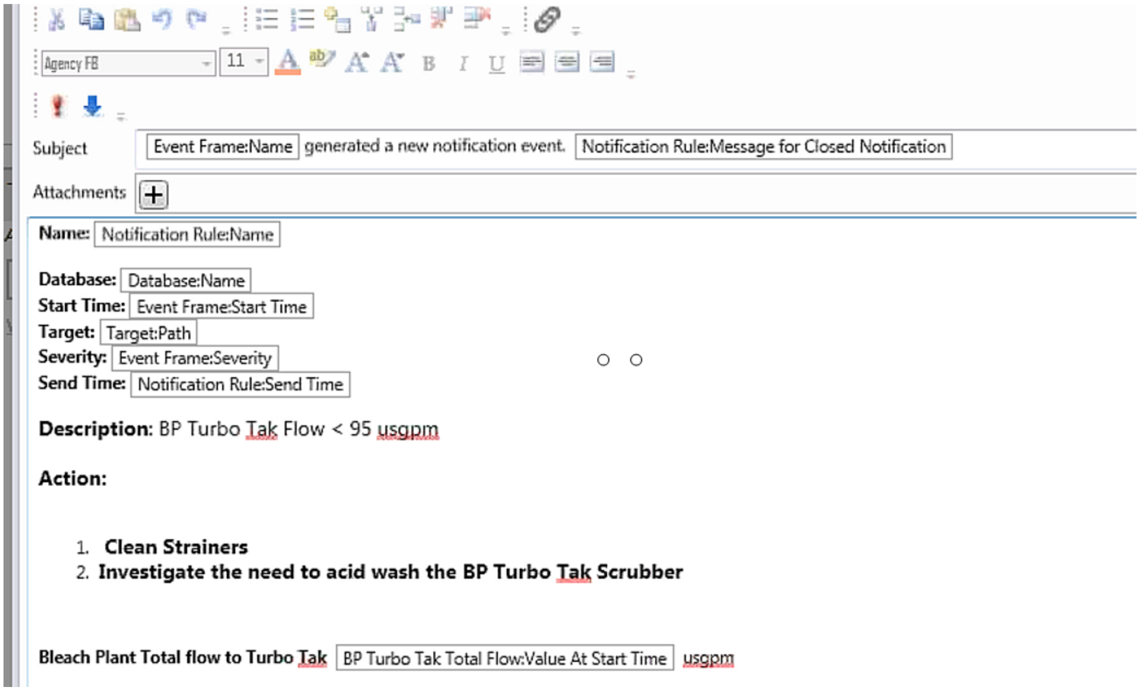
In this exercise, we assess the condition of an equipment by calculating metrics that can serve as leading indicators of equipment failure or loss of efficiency – for example, bearing temperature to evaluate the pump bearing condition.

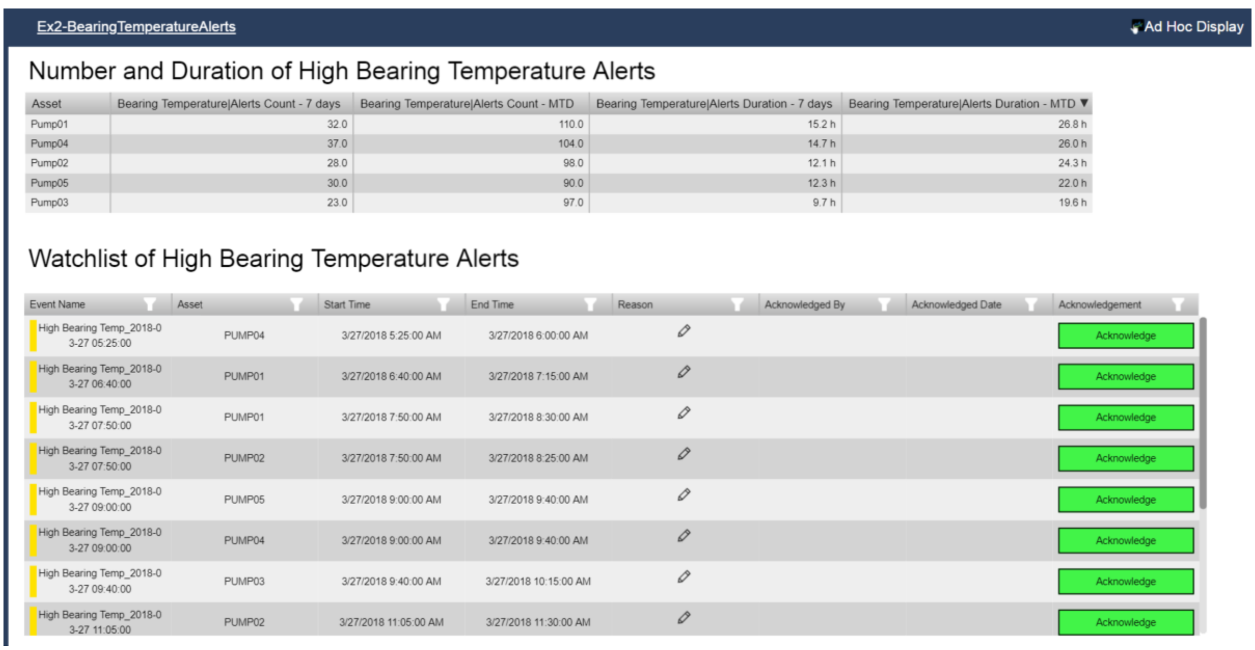
We track the alerts for the bearing temperature and then discuss the use of PI Notification to send an email or use the web service delivery channel to notify a system (i.e. triggering a work order in a work management system such as SAP or IBM Maximo) for follow-up action.

The bearing temperature events are viewed in a watchlist in PI Vision – see screens below.









Number and Duration of High Bearing Temperature Alerts

Asset	Bearing Temperature|Alerts Count - 7 days	Bearing Temperature|Alerts Count - MTD	Bearing Temperature|Alerts Duration - 7 days	Bearing Temperature|Alerts Duration - MTD ▼
Pump01	32.0	110.0	15.2 h	26.8 h
Pump04	37.0	104.0	14.7 h	26.0 h
Pump02	28.0	98.0	12.1 h	24.3 h
Pump05	30.0	90.0	12.3 h	22.0 h
Pump03	23.0	97.0	9.7 h	19.6 h

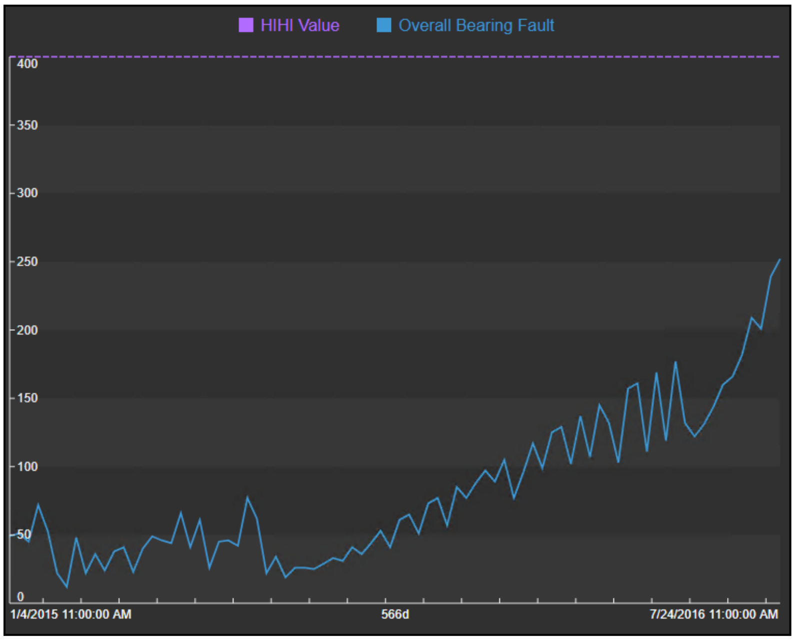
Watchlist of High Bearing Temperature Alerts

Event Name	Asset	Start Time	End Time	Reason	Acknowledged By	Acknowledged Date	Acknowledgement
High Bearing Temp_2018-03-27 05:25:00	PUMP04	3/27/2018 5:25:00 AM	3/27/2018 6:00:00 AM				Acknowledge
High Bearing Temp_2018-03-27 06:40:00	PUMP01	3/27/2018 6:40:00 AM	3/27/2018 7:15:00 AM				Acknowledge
High Bearing Temp_2018-03-27 07:50:00	PUMP01	3/27/2018 7:50:00 AM	3/27/2018 8:30:00 AM				Acknowledge
High Bearing Temp_2018-03-27 07:50:00	PUMP02	3/27/2018 7:50:00 AM	3/27/2018 8:25:00 AM				Acknowledge
High Bearing Temp_2018-03-27 09:00:00	PUMP05	3/27/2018 9:00:00 AM	3/27/2018 9:40:00 AM				Acknowledge
High Bearing Temp_2018-03-27 09:00:00	PUMP04	3/27/2018 9:00:00 AM	3/27/2018 9:40:00 AM				Acknowledge
High Bearing Temp_2018-03-27 09:40:00	PUMP03	3/27/2018 9:40:00 AM	3/27/2018 10:15:00 AM				Acknowledge
High Bearing Temp_2018-03-27 11:05:00	PUMP02	3/27/2018 11:05:00 AM	3/27/2018 11:30:00 AM				Acknowledge

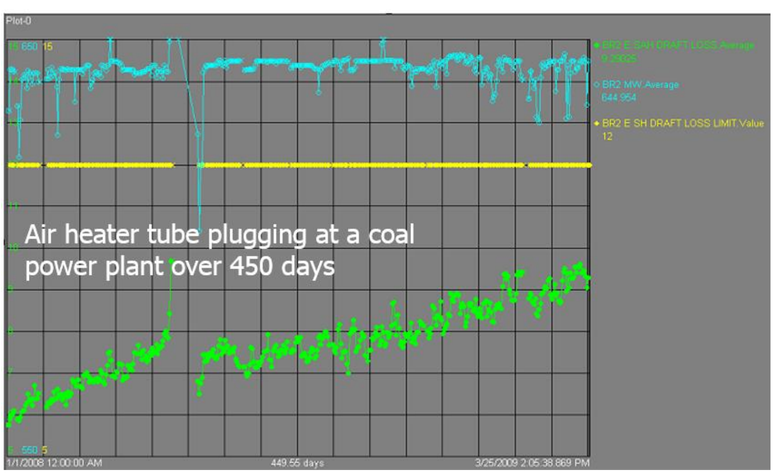
Exercise 3a: Predictive Maintenance (PdM) – Bearing Vibration

For certain classes of process equipment, their condition can be evaluated by monitoring some key metric, such as efficiency for a compressor, fouling for a heat-exchanger, bearing vibration on a pump, etc. Often, these metrics show a pattern with time – and, linear, piece-wise linear or non-linear trend can be extrapolated to estimate remaining-useful-life.

The screen below shows increasing vibration over time (100+ days). The trend can be extrapolated to estimate when it will reach a defined threshold and schedule maintenance.



Another example from a coal power plant air heater is shown below. The green trace (with increasing Delta P) shows the heater tubes getting increasingly plugged over a period of 450 days. The blue trace shows a nominal 650 MW production rate whenever the air heater Delta P is calculated. The yellow trace shows the maximum allowable Delta P i.e. 12 inches of H2O.



Extrapolating the trend (of the green trace) will indicate that you have about 60-90 days before air heater Delta P reaches the maximum allowable limit and should be scheduled for maintenance.

Exercise 3b – Engine failure - CM, PM and PdM (early fault detection via machine learning)

In this Exercise, we will use engine operations data and failure history to guide maintenance decisions, and quantify the benefits when moving from CM to PM to PdM:

- CM - Corrective maintenance - break-fix
- PM - Preventive maintenance - run-hours based
- PdM - Predictive maintenance - early detection (via machine learning - multi-variate condition assessment)

In a deployment with about 100 similar engines, sensor data such as rpm, burner fuel/air ratio, pressure at fan inlet, and twenty other measurements plus settings for each engine – for a total of about 2000 tags – are available. On average, an engine fails after 206 cycles, but it varies widely - from about 130 to 360 cycles – each cycle is about one hour.

With this given failure history for the engines and known costs for PMs vs. repairs, we calculate the benefits in moving from CM to PM to PdM.

As part of the lab, we discuss:

- Can you quantify the $ spent on maintenance with the break-fix strategy (corrective maintenance)?
- A sister company with similar operations, failure history and repair/PM costs uses the median failure rate of 199 cycles for PMs. Should you adopt this?
- Can you do better? If so, after how many cycles will you do the PMs?
- Can you quantify the benefits in moving from corrective to run-hours based PMs?
- If engine operations data can be used for early detection of failure – say, within 20 cycles of a failure with 100% certainty – if and how much will you save by using PdM vs the PM approach

For details of PdM model development, i.e. early fault detection via machine learning for predicting failure within a window of time, see…more.

Exercise 4: Multiple condition assessment rules and asset health score

In this Exercise, you apply the appropriate condition assessment rules and corresponding weighting factors to process/equipment measurements to calculate an overall asset health score.

It uses AF Analytics to convert a "Raw Value" (sensor data) to a normalized i.e. a "Case Value". And then, by applying a Weight%, it is transformed to a Score.

Each measurement gets a normalized weighted score (0 to 10) by applying a condition assessment rule. And, then the normalized scores are rolled up to arrive at a composite asset health score. The Weight% applied to each attribute depends on its contribution to the overall asset health.

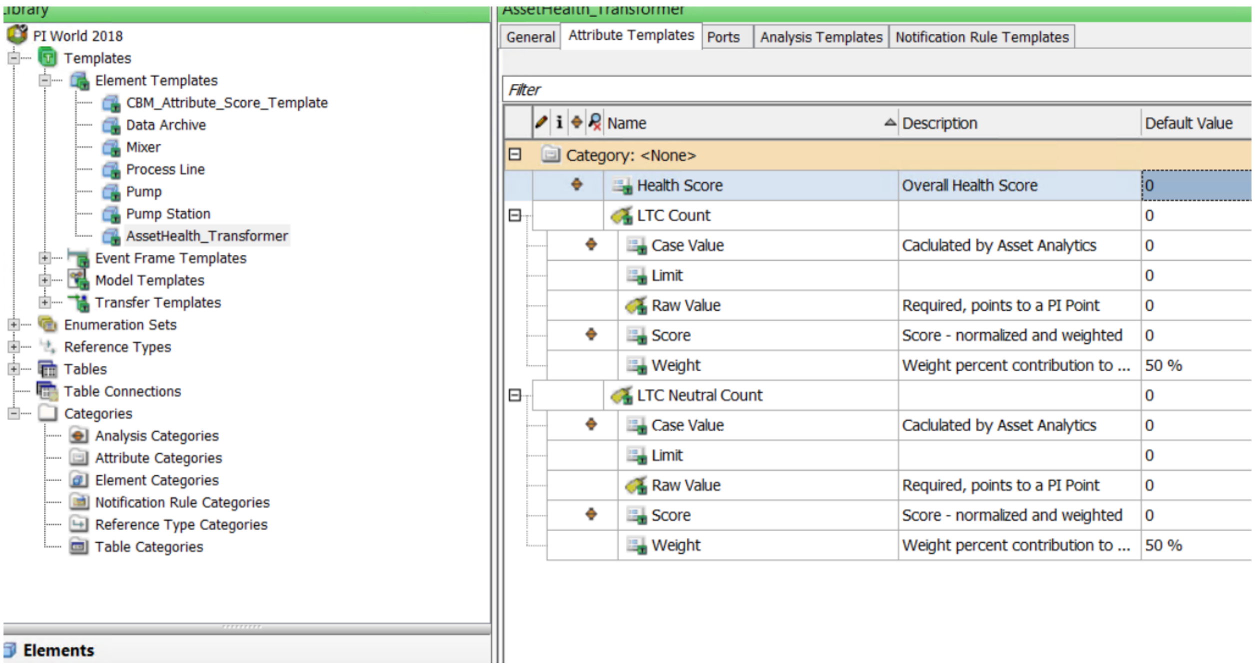
The composite asset health score ranges from 0 to 10 (0=Good, 10=Bad)

A Transformer asset health score example is used with the following measurements:

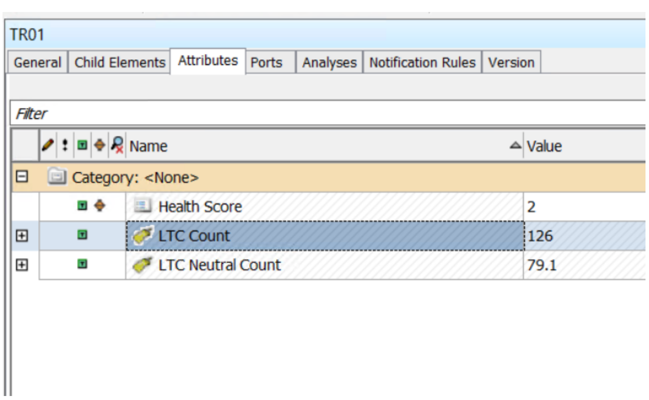
- LTC (Load Tap Changer) counter operations

- LTC through neutral count
- DGA (dissolved gas analysis) detectable acetylene
- DGA high gas rate of change
- Low dielectric
- High water
- Low nitrogen pressure

An example Transformer template is shown below:



And, as you configure Transformers using these templates, the composite health score is periodically calculated by PI System Asset Analytics.



The composite health score for transformer TR01 is 2 i.e. asset is in good health (0=Good, 10=Bad).

PI System software

The VM (virtual machine) used for this lab has the following PI System software installed:

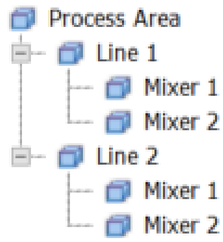
Software	Version
PI Data Archive	2018 SP3
PI Asset Framework (PI AF) server	2018 SP3
PI Asset Framework (PI AF) client (PI System Explorer)	2018 SP3
PI Analysis & PI Notifications Services	2018 SP3
PI Vision	2019
PI Web API	2019

For additional details regarding PI System software, please see:
http://www.osisoft.com/pi-system/pi-capabilities/product-list/

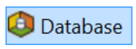
Exercise 1 – Usage-based Maintenance

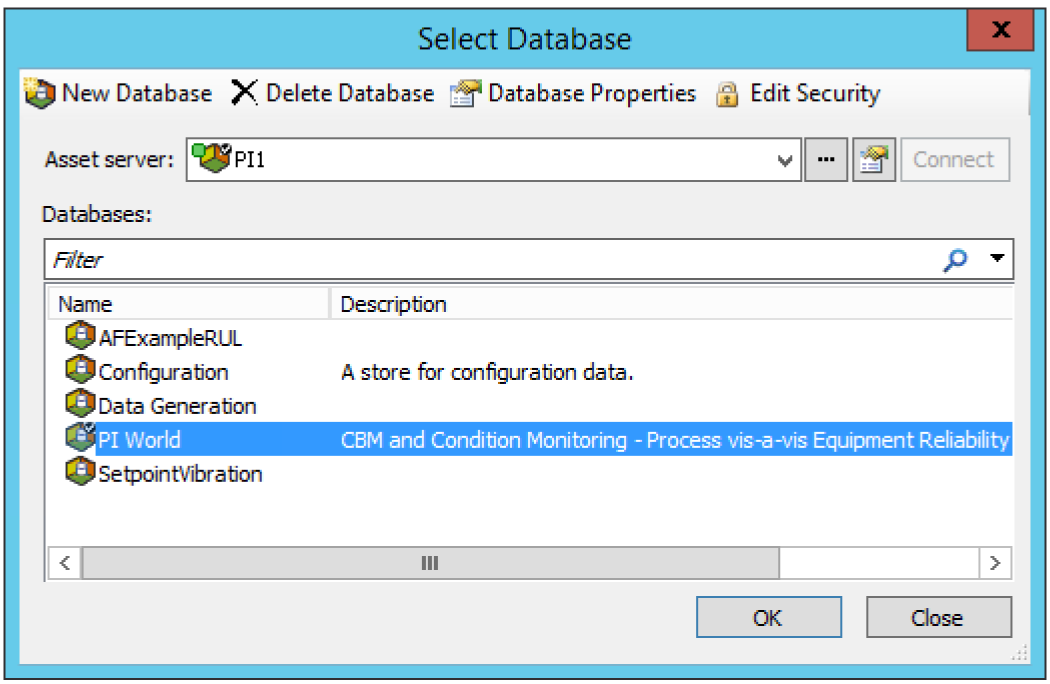
In this exercise, equipment run-hours and valve actuation counts are calculated to serve as a basis for usage-based maintenance.

There are two process lines in an ice-cream factory – Line 1 and Line 2, with two mixers on each line.

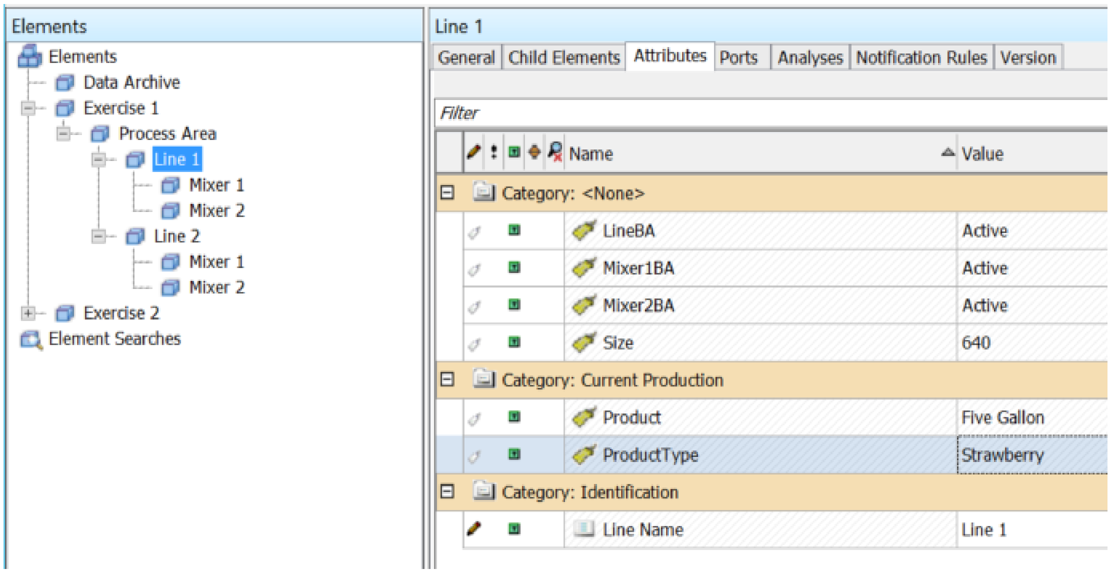


Step 1: Exploring the Asset Framework structure

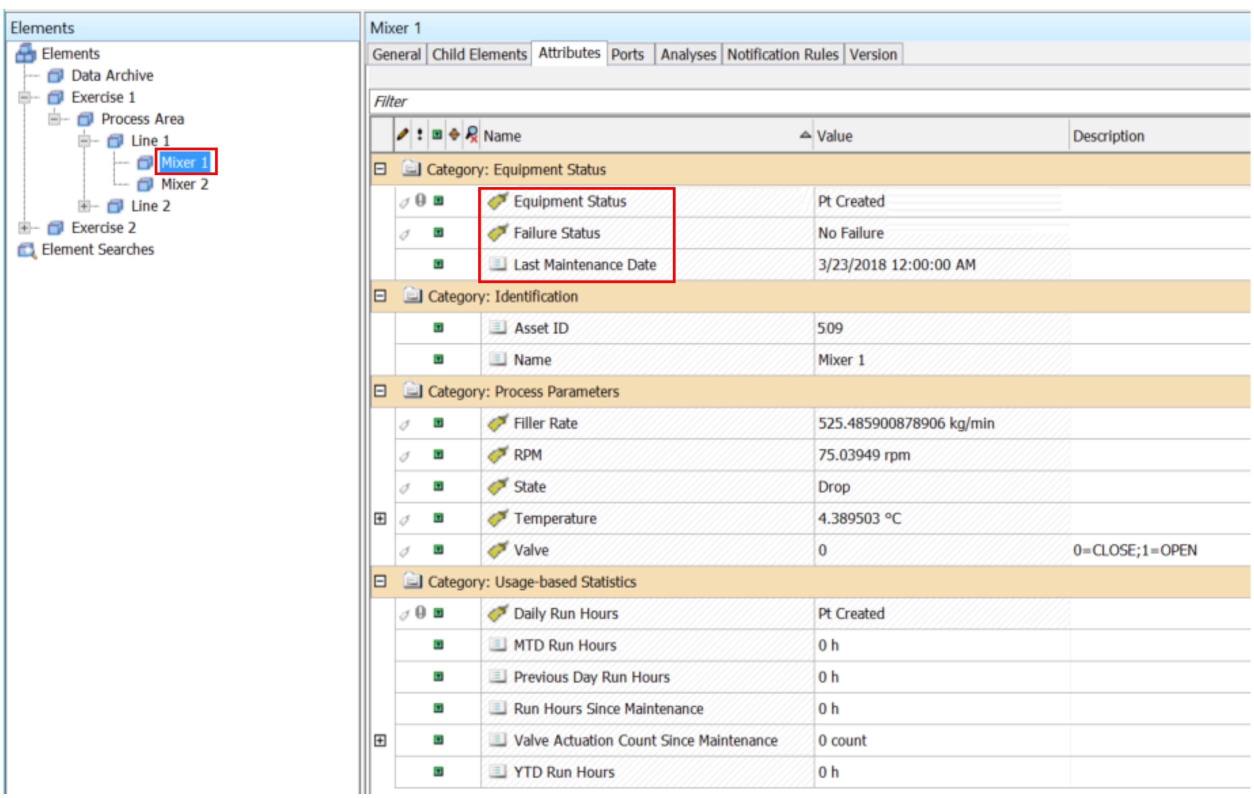
1. Open **PI System Explorer**; connect to the **PI World** AF database.
   If the top bar of the PI System Explorer window does not already show **\\PI1\PI World**, then click on the top toolbar  button to select the PI AF database named **PI World**.



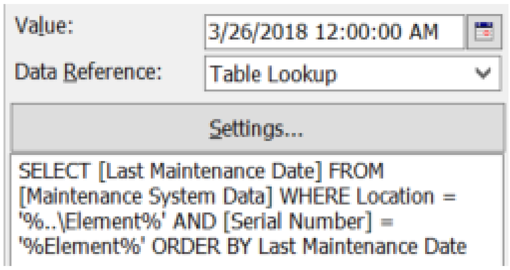
2. From the **Elements** section, navigate to **Exercise 1 > Process Area > Line 1**.
   The **Attributes** tab shows the current production on Line1.



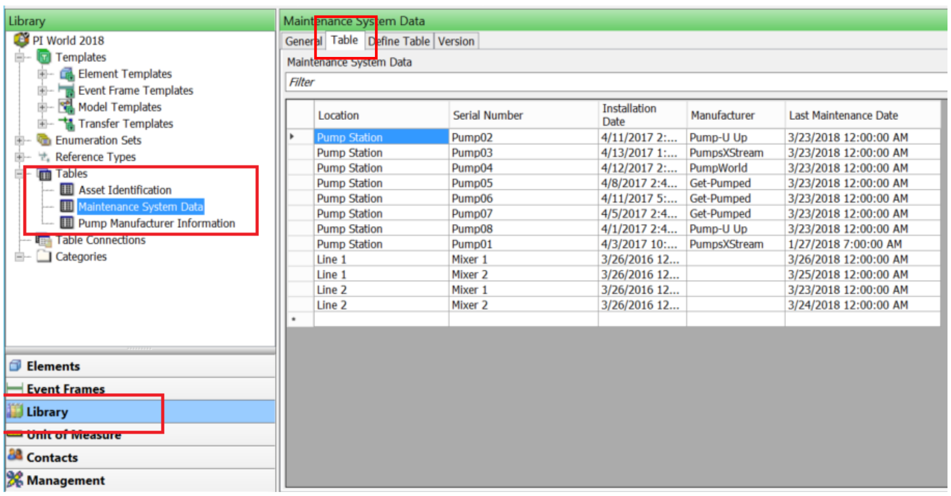
3. Drill-down under Line 1 > **Mixer 1**, then click on the **Attributes** tab for Mixer 1.



a. Note the **Last Maintenance Date** attribute.
   Review the attribute configuration (in the right-side panel); SELECT statement retrieves the date from a table.



b. To view the full table, go to the **Library** section of PI System Explorer, under **Tables > Maintenance System Data** section.
   Select the **Table** tab to visualize the data.
   Typically, this table queries an external system such as your maintenance database and is refreshed with new values on a periodic basis.



Location	Serial Number	Installation Date	Manufacturer	Last Maintenance Date
Pump Station	Pump02	4/11/2017 2:...	Pump-U Up	3/23/2018 12:00:00 AM
Pump Station	Pump03	4/13/2017 1:...	PumpsXStream	3/23/2018 12:00:00 AM
Pump Station	Pump04	4/12/2017 2:...	PumpWorld	3/23/2018 12:00:00 AM
Pump Station	Pump05	4/8/2017 2:4...	Get-Pumped	3/23/2018 12:00:00 AM
Pump Station	Pump06	4/11/2017 5:...	Get-Pumped	3/23/2018 12:00:00 AM
Pump Station	Pump07	4/5/2017 2:4...	Get-Pumped	3/23/2018 12:00:00 AM
Pump Station	Pump08	4/1/2017 2:4...	Pump-U Up	3/23/2018 12:00:00 AM
Pump Station	Pump01	4/3/2017 10:...	PumpsXStream	1/27/2018 7:00:00 AM
Line 1	Mixer 1	3/26/2016 12...		3/26/2018 12:00:00 AM
Line 1	Mixer 2	3/26/2016 12...		3/25/2018 12:00:00 AM
Line 2	Mixer 1	3/26/2016 12...		3/23/2018 12:00:00 AM
Line 2	Mixer 2	3/26/2016 12...		3/24/2018 12:00:00 AM

c. Note the **Failure Status** attribute. This will be used in later calculations and is simple Boolean denoting a Failure.

Each ice-cream mixer has a motor; its RPM (revolutions per minute) is measured.

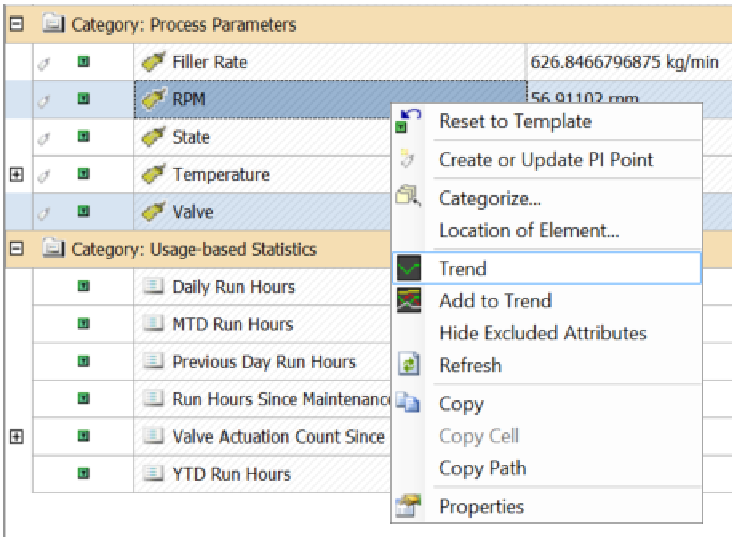
A valve is opened to allow the product to flow in and be mixed. We would like to calculate the running hours for the mixers but there is no direct measurement to indicate the running/idle status of the mixer.

Step 2: Creating a Status attribute

The mixer is inferred to be "in production" when it is "running" and the valve is open.

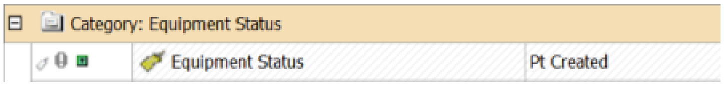
Let's create an analysis to store the equipment status. We also know that the equipment provides a failure indicator which can be useful for OEE type calculations.

1. Go to the **Elements** section of PI System Explorer, under our **Line 1 > Mixer 1** equipment. Look at the **RPM** and **Valve** attributes.
   Select both attributes using the Ctrl key on your keyboard, and then right-click one of the two attributes to select **Trend**.



   Note the RPM in blue and Valve status in red.
   The equipment is "in production" when both the valve is open (value=1) and the RPM has a positive value (value>0).

2. Note **Equipment Status** attribute that we have created as a placeholder for the status of the equipment. It shows "Pt Created" as no value has been written to it yet.

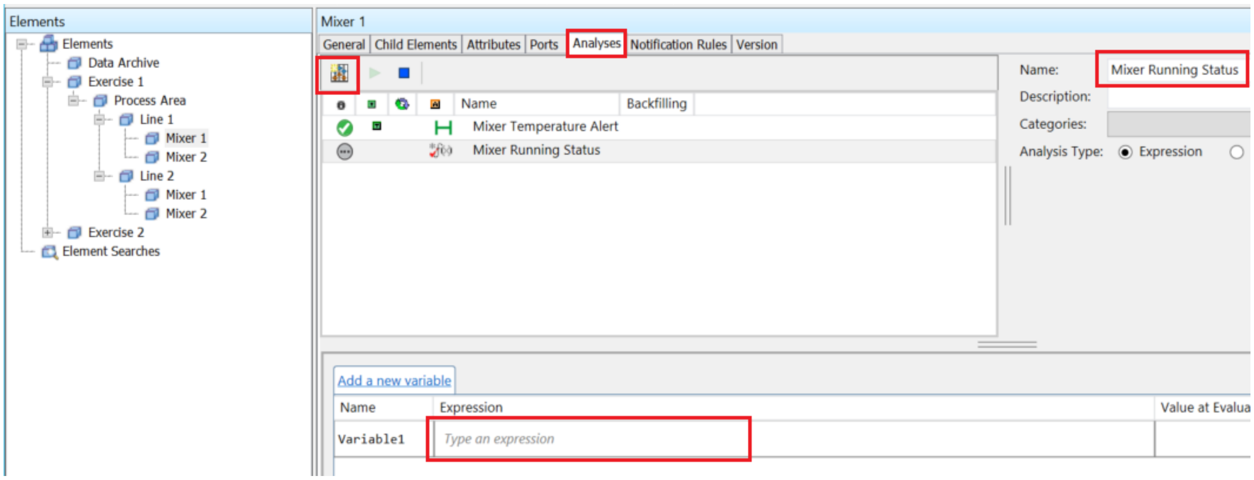


3. This Equipment Status attribute uses an enumeration set called **Equipment Status**, where:

Value	Name
0	Idle
1	Running
2	Failure

   The Enumeration set is available from Library > Enumeration Sets > Equipment Status.

4. Switch to the **Analyses** tab for Mixer 1 and create a new Expression analysis called **Mixer Running Status**.

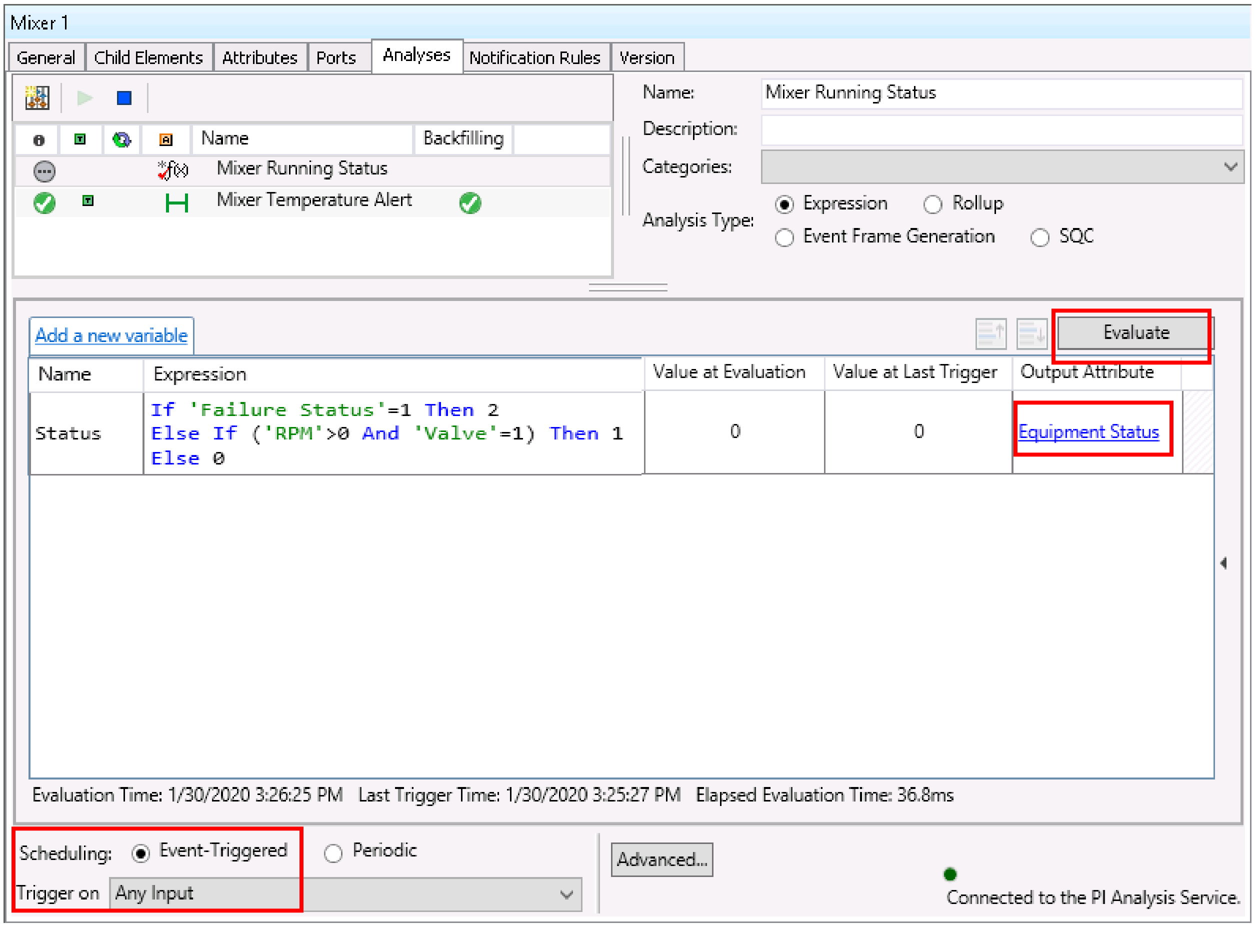


5. To configure this expression, we use the RPM attribute, the Valve attribute, and the Failure Status attribute.
   a. In the Variable1 expression field, enter the following; you can use the "intellisense" like prompts to speed up the process of writing this expression.

Name	Expression
Status	If 'Failure Status'=1 Then 2 Else If ('RPM'>0 And 'Valve'=1) Then 1 Else 0

Note: Use Shift+Enter to start a new line while writing an Analysis Expression. Use // in front of a line to mark it as a comment.

   b. Map the expression result to the **Equipment Status** attribute (see next picture).
   c. Leave the scheduling option to **Event-Triggered** and **Any Input**.
   d. Click the **Evaluate** button to check the current value.

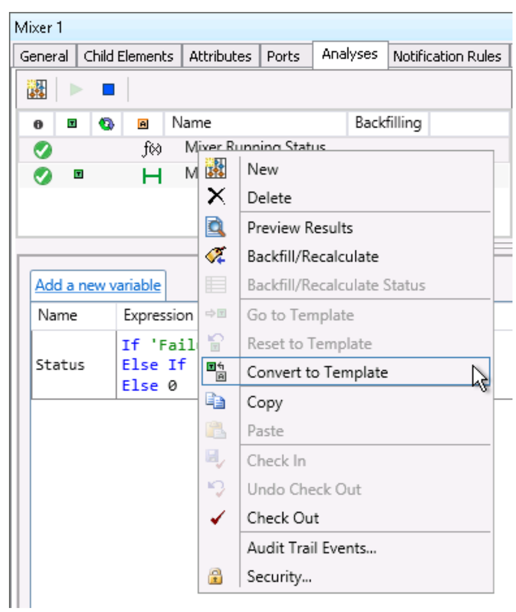


e. Click the Check In button in the top toolbar to save the changes. The analysis will attempt to start and show Running (green checkmark) if no error is present.

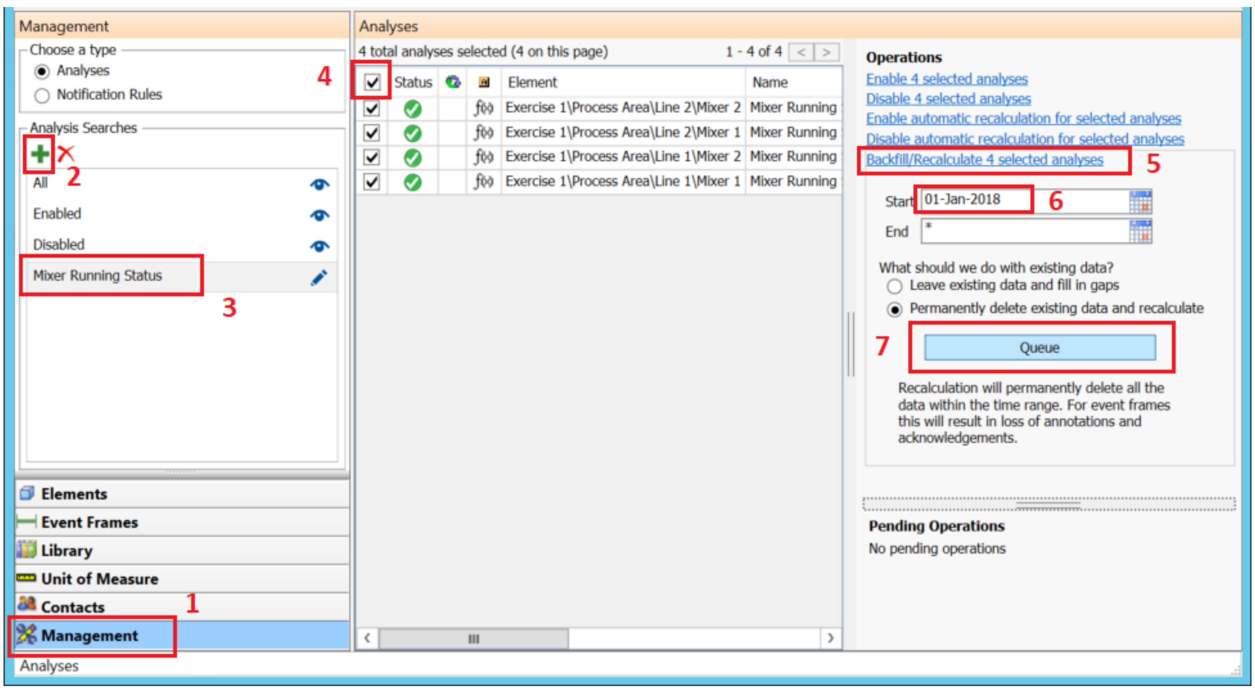
6. The expression is currently only available to Mixer 1.
   To enable it for all other mixers, right-click the **Mixer Running Status** analysis and select **Convert to Template**.

   Next, click on Check In to save the changes.

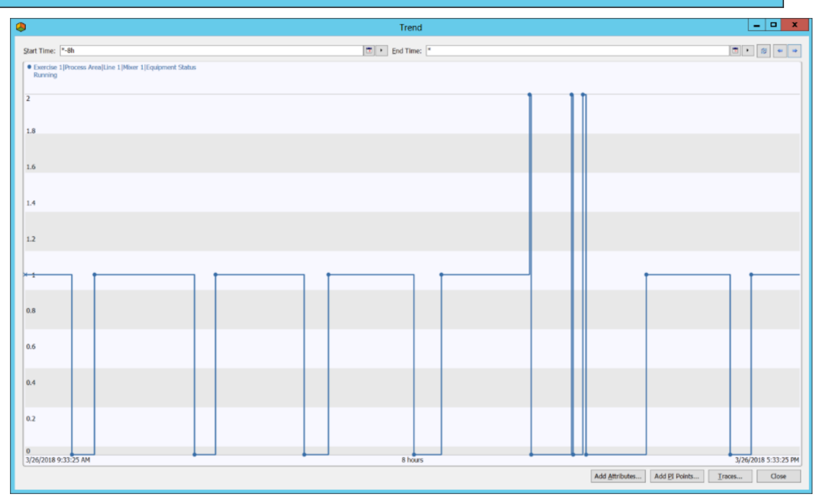
   The calculations can now be applied to all four mixers



7. We will now backfill the status attribute since the beginning of the year (since 01-Jan-2020). From the **Management** section of PI System Explorer, select (see below picture for guidance):
    1. Management
    2. The **Plus** sign to add an analysis search
    3. Enter a name like **Mixer Running Status** and add a search criterion where the **Name = Mixer Running Status** (or the name you gave the analysis created in the previous step). Once created, make sure to select it to filter the list of retrieved analyses in the center.
    4. Check the checkbox to select the four (4) Mixer Running Status analyses.
    5. Click the **Backfill/Recalculate 4 selected analyses** link.
    6. Enter a start date of **First day you started this course** and leave the end date to * (right now).
    7. Click the **Queue** button to start the backfilling.



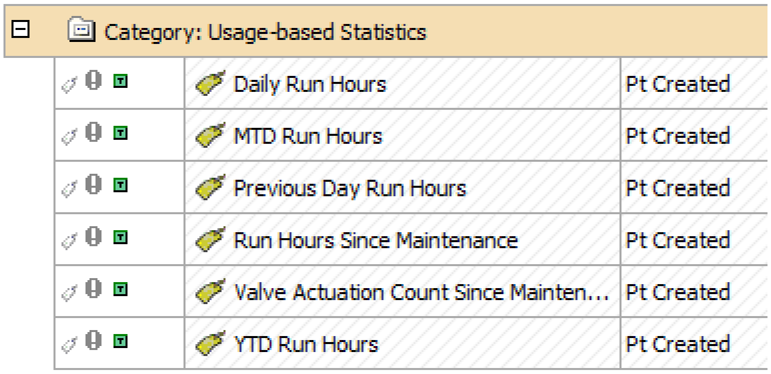
8. Confirm that the backfill was successful; in the **Elements** section, look at the **Equipment Status** attribute of Line 1 > Mixer 1 (0=Idle, 1=Running, 2=Failure). Right-click on the attribute to select **Trend**. View the equipment status for the last 8 hours, from ***-8h** to *.



Step 3: Creating usage-based run hours attributes

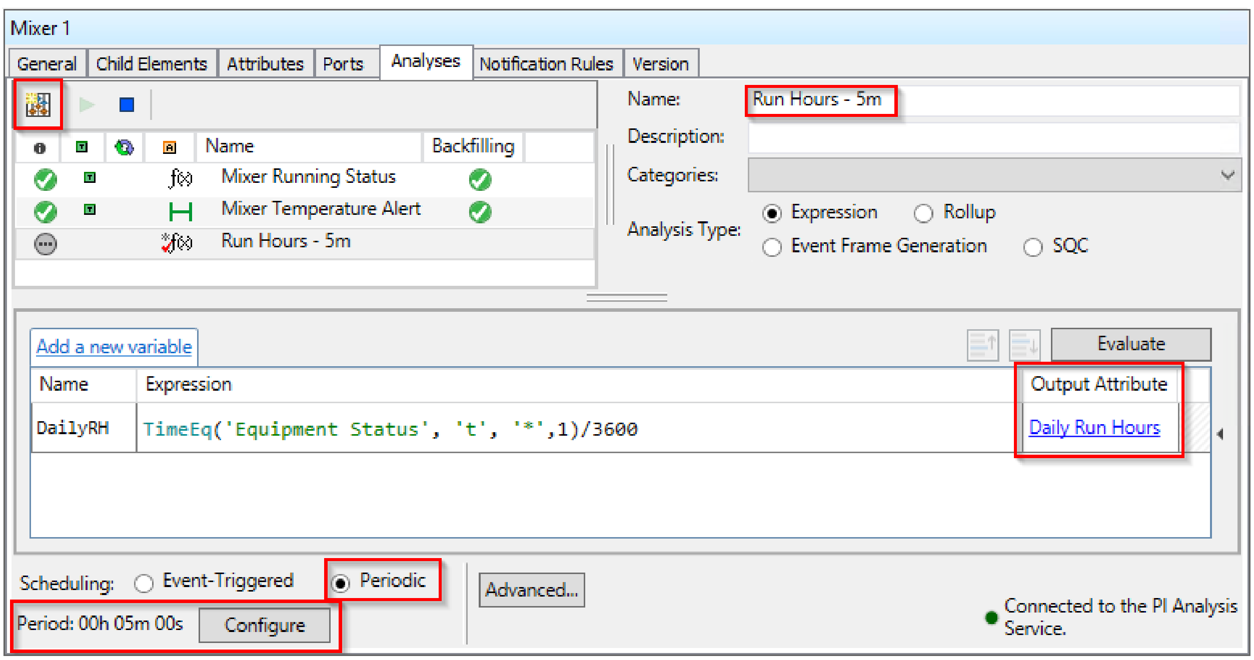
Now that we have an equipment status attribute, we can use it to create usage-based counters for different time ranges (daily, previous day, MTD, YTD, etc.).

1. From the Elements section, select a Mixer and look at its attributes under the **Usage-based Statistics** category.



   We will first populate the run-hours attributes with an analysis, then the valve actuation count with a second analysis.

2. For the run-hours attributes, navigate to the **Analyses** tab for **Exercise 1 > Line 1 > Mixer 1** and create a new Expression analysis named **Run Hours – 5m**.
3. Complete the expression and map the output as follows:

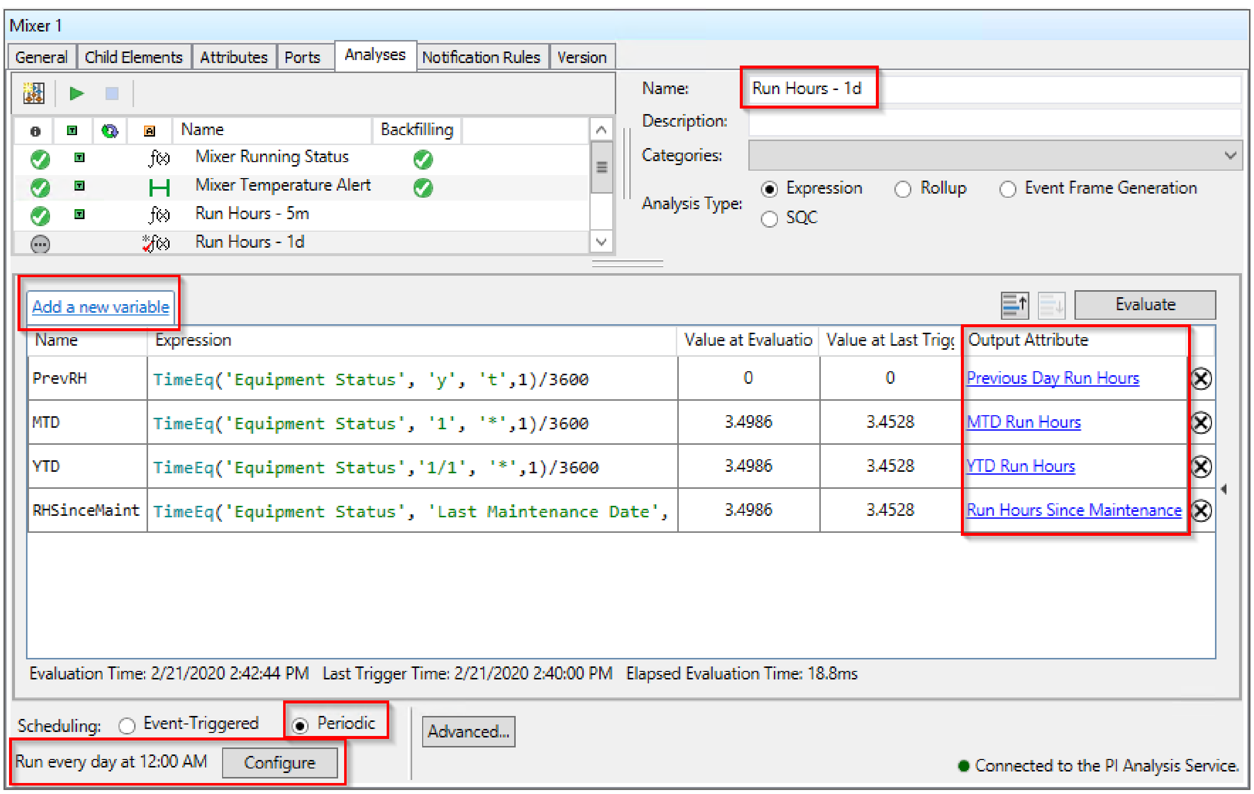


The TimeEq() function calculates the total time in seconds, within a range, that an attribute value is equal to a specified value. In our case, we are looking for the time where the Equipment Status attribute was equal to 1 (where 1=Running).

Note: In Expressions, PI Time Format can be used to specify relative times. For instance, '*' means now, 't' means today at midnight, 'y' means yesterday at midnight, and '1' means the first day of the current month at midnight.

Name	Expression	Description
DailyRH	TimeEq('Equipment Status', 't', '*',1)/3600	Today's run hours.

4. Configure the scheduling to be **Periodic**, every 5 minutes. This is probably too often for a production environment, but for the purpose of the lab, we want the results to be written quickly.
5. Click the **Evaluate** button to ensure no error is present. Next, click the top-toolbar Check In button to save the changes and start the analysis.
6. Right-click the **Run Hours – 5m** analysis and select **Convert to Template** to create it for the other mixers as well. Again, click on the Check In button to commit the changes.
7. For the rest of the calculations we don't need results every 5 minutes, but instead will calculate them daily. Since these Analyses will be similar we can copy and past the recently completed Analysis and rename it **Run Hours – 1d**.
8. Use the **Add a new variable** link above the expressions section to add multiple rows/expressions to have four (4) rows. We will add the expression and map it to the correct attributes.



Name	Expression	Description
PrevRH	TimeEq('Equipment Status', 'y', 't',1)/3600	Yesterday's run hours.
MTD	TimeEq('Equipment Status', '1', '*',1)/3600	Month-to-date run hours, '1' meaning the first day of the current month.
YTD	TimeEq('Equipment Status', '1/1', '*',1)/3600	Year-to-date run hours, '1/1' meaning January 1st of the current year.
RHSinceMaint	TimeEq('Equipment Status', 'Last Maintenance Date', '*',1)/3600	Run hours since the last maintenance date attribute value.

Note: These calculations, especially Year-To-Date (YTD) can be very expensive on the Analysis service. It is recommended to execute them periodically to ensure you have control on how often they are being triggered.

Another way to lessen the load of these calculations is to create a Run Hours totalizer analysis that would increment the lifetime or YTD run hours every day at midnight, and where the expression will be:

PreviousDayLifetimeTotal + DailyRunHours = NewLifetimeTotal

9. Click the **Evaluate** button to ensure no error is present. Next, click the top-toolbar Check In button to save the changes and start the analysis.
10. Right-click the **Run Hours – 1d** analysis and select **Convert to Template** to create it for the other mixers as well. Again, click on the Check In button to commit the changes.

Step 4: Creating a usage-based counter (valve actuation)

A valve, like other pieces of equipment, can wear out with usage by actuation.

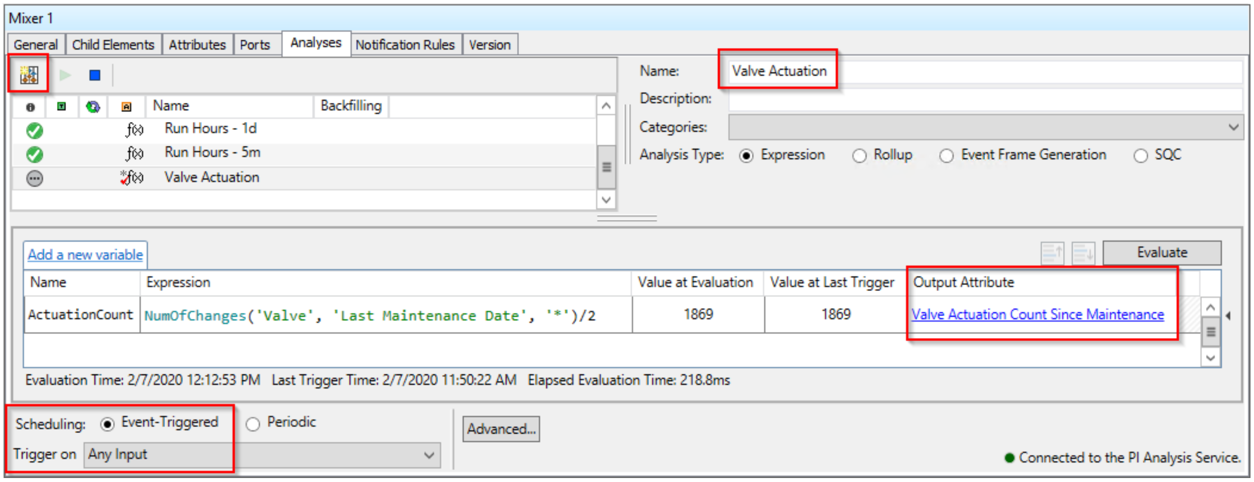
The valve on each mixer has a status shown in the **Valve** attribute, Close=0 and 1=Open.

We will create an analysis to count the number of 0-1 occurrences since the last maintenance date. As in the previous step, this calculation can be performed on different time ranges. Note that we will assume the same maintenance date for the whole asset, although you could have different maintenance dates for different components of an asset.

1. Under the **Analysis** tab, create a new expression analysis, named **Valve Actuation**.
2. Use the **NumOfChanges()** expression to calculate the number of actuations that occurred on the valve since the last maintenance date. The NumOfChanges() function returns the number of changes in value for an attribute within a specified time range. It will not consider equal consecutive values as a change (for example if a PI Tag was receiving and recording consecutive 1 values as in 0-1-1-1-1-1-0-1-0, this would count for 4 changes). We are dividing by 2 as NumOfChanges() will count the 0-1 and the 1-0 as changes.

Name	Expression
ActuationCount	NumOfChanges('Valve', 'Last Maintenance Date', '*')/2

3. Map the expression to the **Valve Actuation Count Since Maintenance** attribute.
4. Leave the scheduling to **Event-Triggered** and **Any Input**. The calculation result may come in a little while since it will be performed only when the Valve attribute will get a new value.



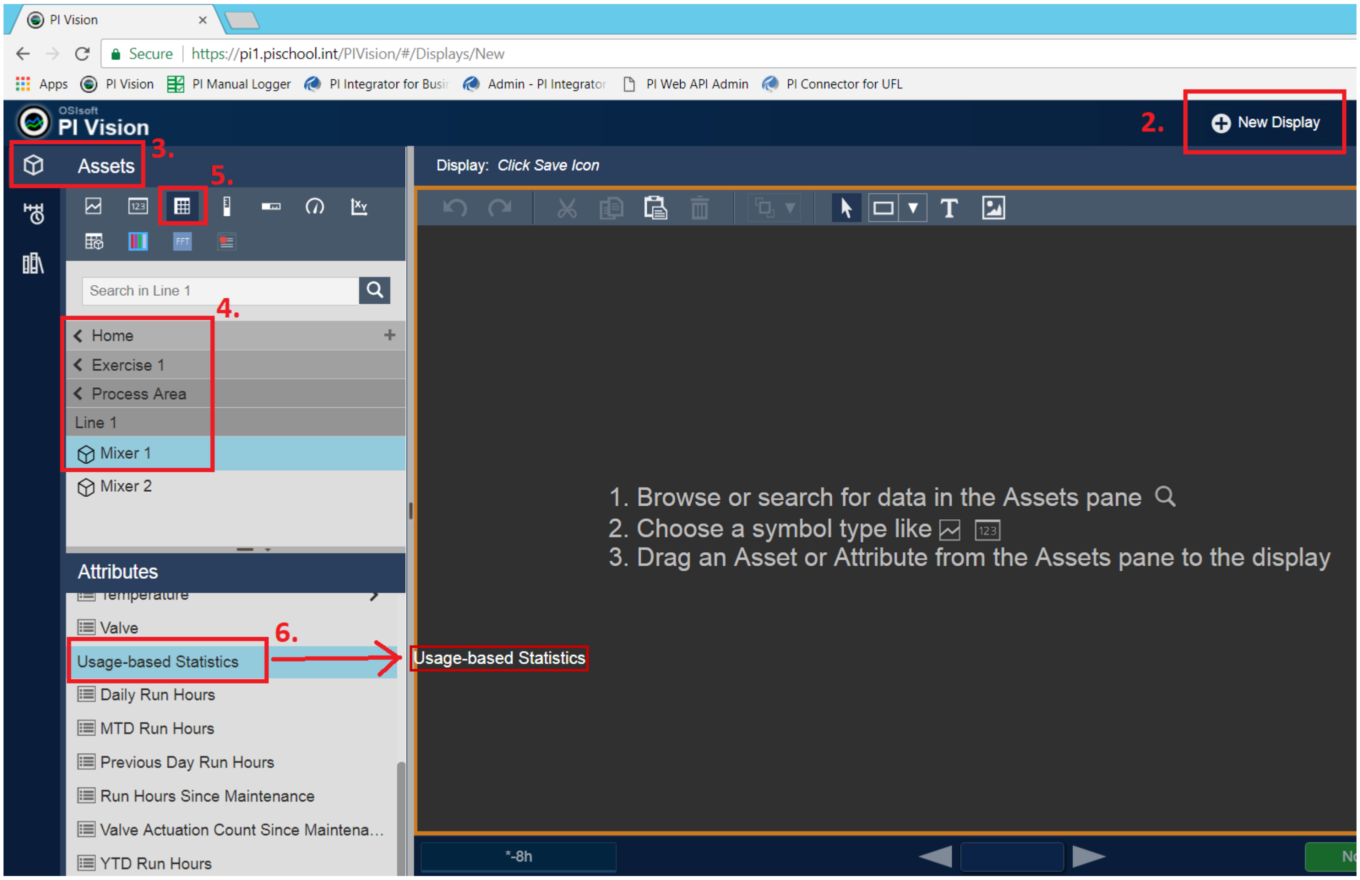
5. Evaluate the expression and if successful, click the Check In button to save the changes and start the analysis.
6. Right-click the **Valve Actuation** analysis to select **Convert to Template**. Click a second time on the Check In button to commit the changes.
7. Check the result from the **Attributes** tab (again it may take a while before the value shows up, use the **Refresh** button from the top toolbar to force a refresh of the attributes value).

Note: Similarly, a counter for the number of failures on the equipment can be created and used towards usage-based maintenance trigger. This will be explored as part of Exercise 2.

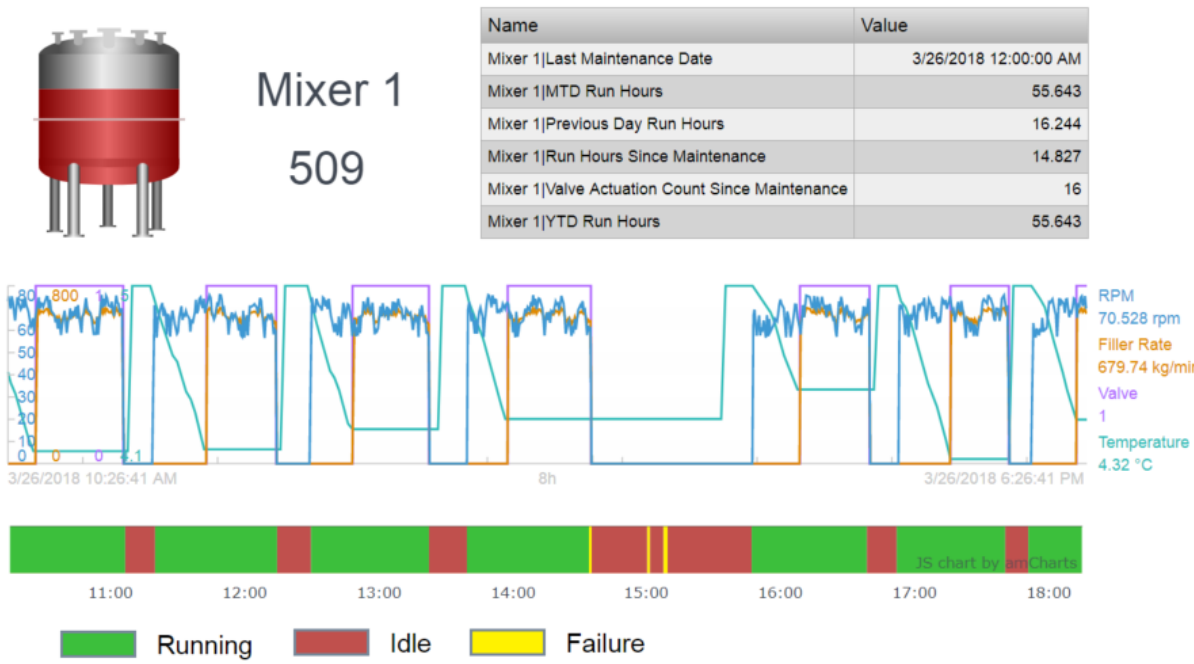
Step 5: (Optional) Comparing equipment on their usage-based statistics

We will use PI Vision to compare the status and the run hours and valve actuation attributes for the four mixers.

1. Open **Google Chrome** from the taskbar shortcut and then click on the **PI Vision** shortcut from the Bookmarks bar (this will bring you to https://pi1.pischool.int/PIVision).
2. You can explore the displays available, but for this step, click the **+ New Display** button in the top upper right.
3. Select the **Assets** pane on the left side.
4. Drill-down (click on the ">") to **PI World > Exercise 1 > Process Area > Line 1 > Mixer 1**.

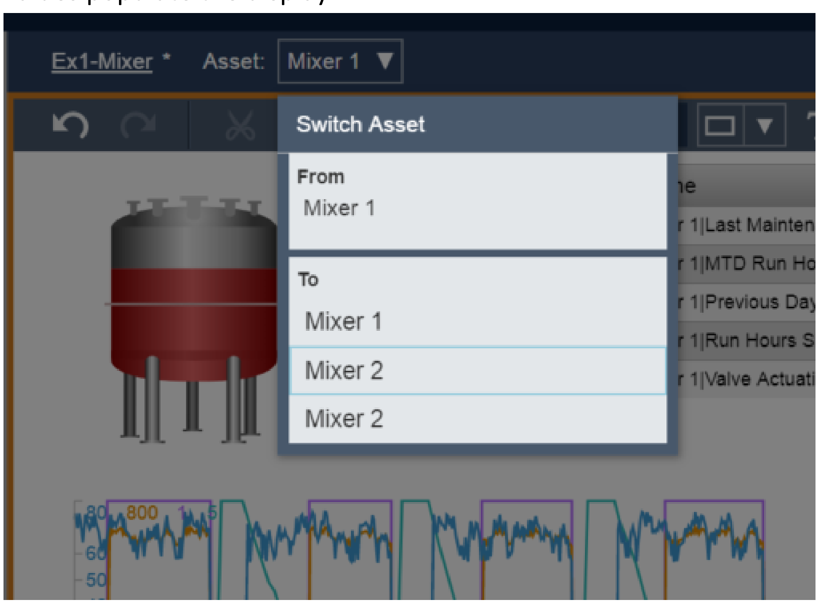


5. Select the **Table** symbol () at the top.
6. Drag and drop the Usage-based Statistics category on the display. You can right-click the table that was added and select **Configure Table**, to keep only the **Name**, **Value**, and **Units** columns, and customize the formatting of the display.
7. You can then add the **Process Parameters** with a **Trend** symbol (), and also use the custom **String Values Plot** symbol () to show the **Equipment Status** attribute.
8. The end result could look similar to (note the tank symbol is coming from the **Graphic Library** left-side pane (), under the **Tanks** section):

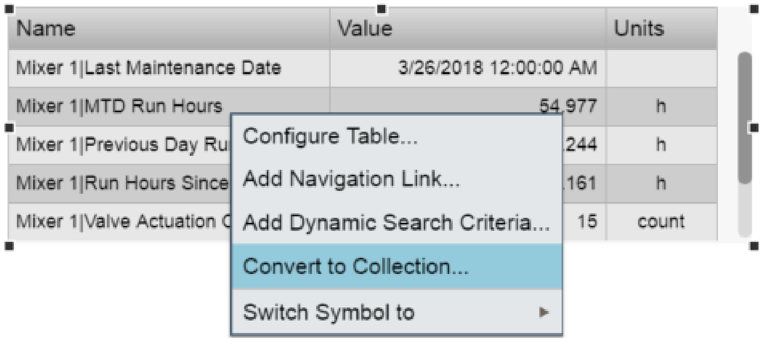


Name	Value
Mixer 1|Last Maintenance Date	3/26/2018 12:00:00 AM
Mixer 1|MTD Run Hours	55.643
Mixer 1|Previous Day Run Hours	16.244
Mixer 1|Run Hours Since Maintenance	14.827
Mixer 1|Valve Actuation Count Since Maintenance	16
Mixer 1|YTD Run Hours	55.643

9. Once completed, use the **Switch Asset** drop-down to select another Mixer and see the new values populate the display.

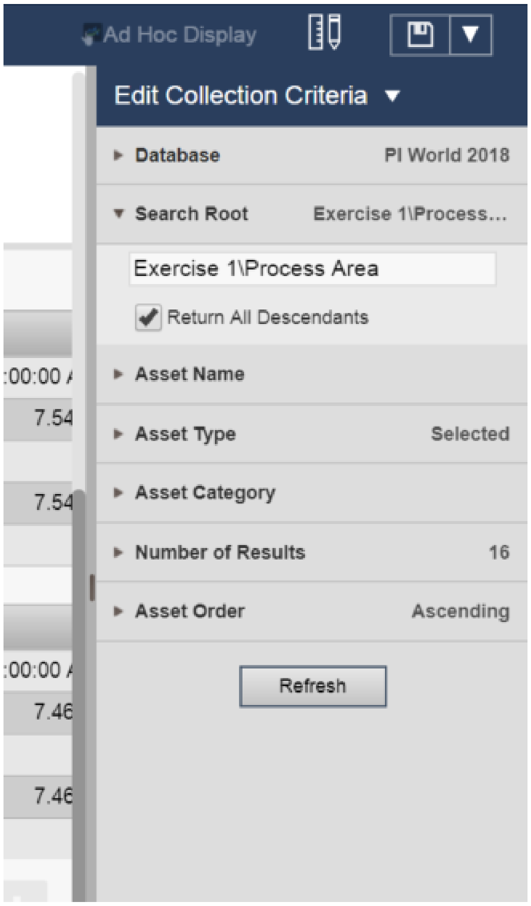


10. It is possible to have the statistics for all four mixers side by side. Simply right-click the Table symbol and select **Convert to Collection…**



11. Make sure to resize the Collection symbol that was created to show all four (4) tables.

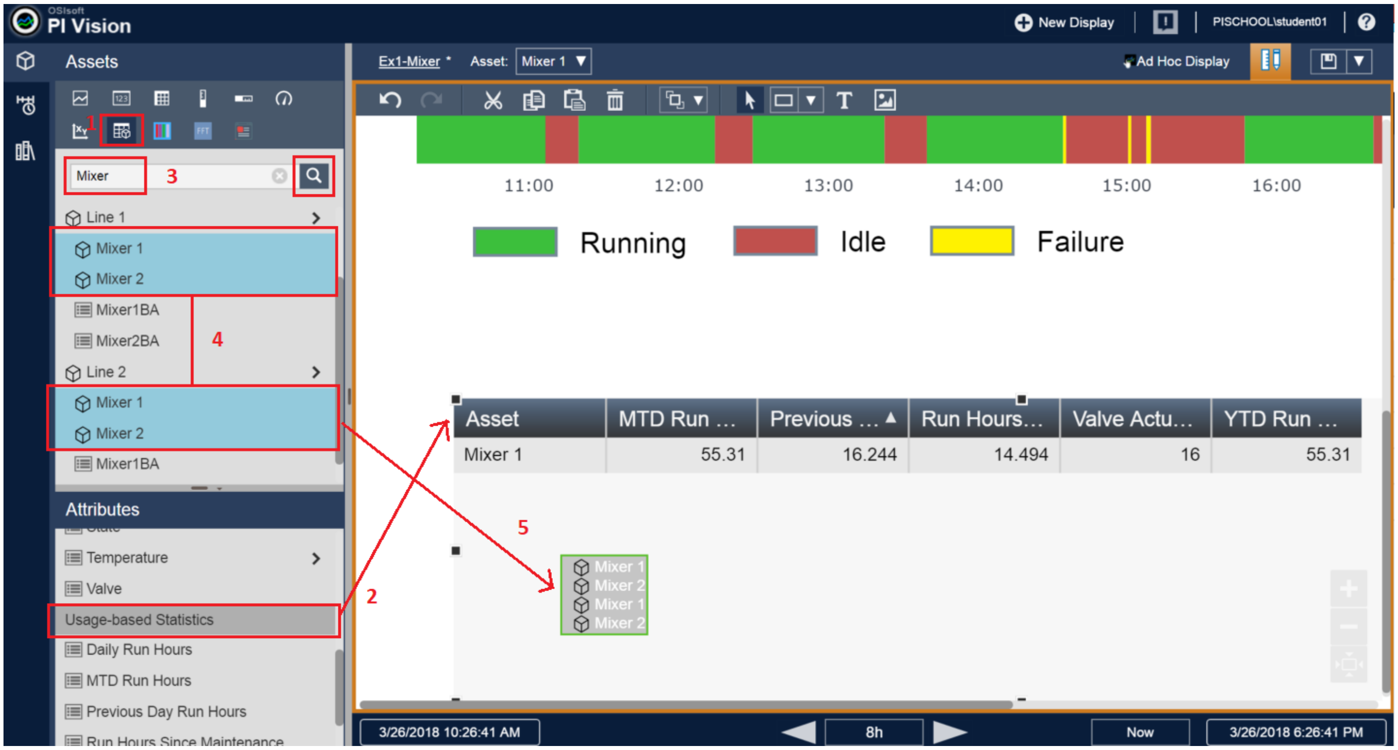
12. In order to show all four mixers, you may need to right-click the Collection that was created, select the **Edit Collection Criteria…** and modify the **Search Root** field like in the below picture (remember to check the **Return All Descendants** option):



Then click the **Refresh** button. Resize the symbol to show all four (4) mixers information.

13. Another way, to compare the statistics, but this time in one table, is to use the **Asset Comparison Table** symbol.

    1. Select the **Asset Comparison Table** symbol ().
    2. Drag the whole **Usage-based Statistics** attribute category on the display.
    3. Search for mixer under the Process Area level in the hierarchy to find all four mixers.
    4. Using the **Ctrl** key, multi-select the four mixers.
    5. Drag the four mixers over the Asset Comparison Table to add all four to the symbol.



Once all four assets are added, it is possible to order by one of the columns by clicking on the column header of interest (make sure the display is not showing the edit symbol () in its upper-right corner to use this functionality).

Asset	Asset ID	MTD Run...	Previous D...	Run Hours...	Valve Actu...	YTD Run ...	Daily F
Mixer 2	510	56.055	16.317	30.9	34	56.055	Pt
Mixer 1	509	55.477	16.244	14.661	16	55.477	Pt
Mixer 1	609	7.7722	0	7.7722	62	7.7722	Pt
Mixer 2	610	7.7106	0	7.7106	53	7.7106	Pt

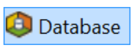
Exercise 2 – Condition-based Maintenance

In this exercise, we assess the condition of an equipment by calculating metrics that can serve as leading indicators of equipment failure or loss of efficiency – for example, bearing temperature to understand the pump bearing condition.

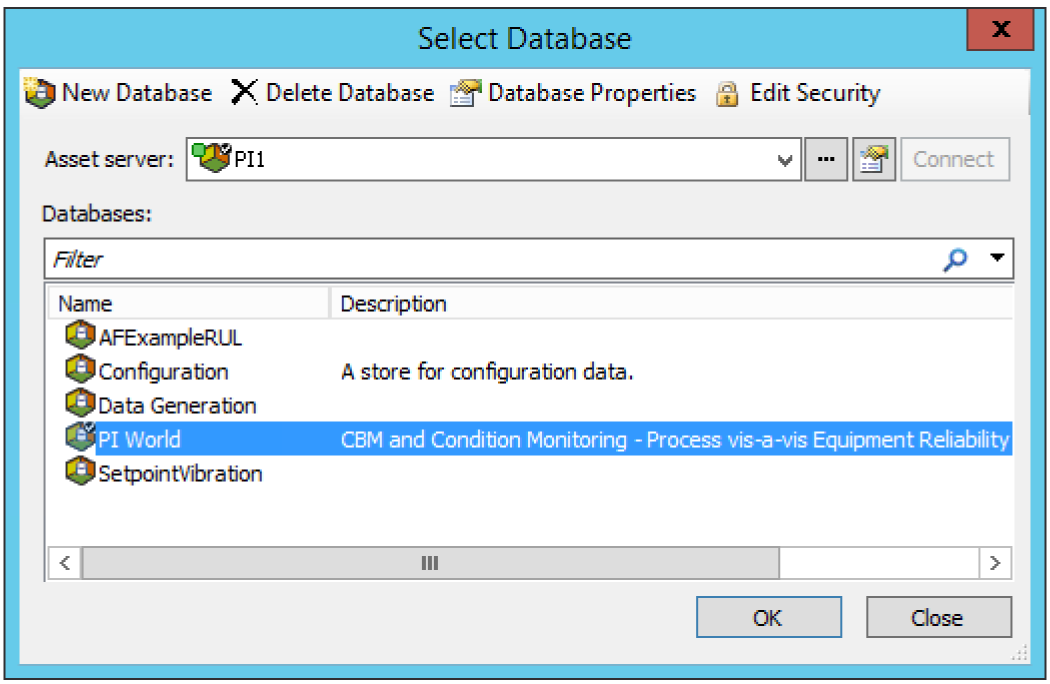
We track the alerts for the bearing temperature and then discuss the use of PI Notification to send an email or use the web service delivery channel to notify a system (i.e. triggering a work order) for follow-up action. The bearing temperature events are viewed in a watchlist in PI Vision.

First, look at usage-based information in AF structure used for this exercise.

Step 1: Exploring the Asset Framework structure

1. Open **PI System Explorer** and connect to the **PI World** AF database. If the top bar of the PI System Explorer window does not show \\PI1\PI World already, then click on the top toolbar 

button to select the PI AF database.

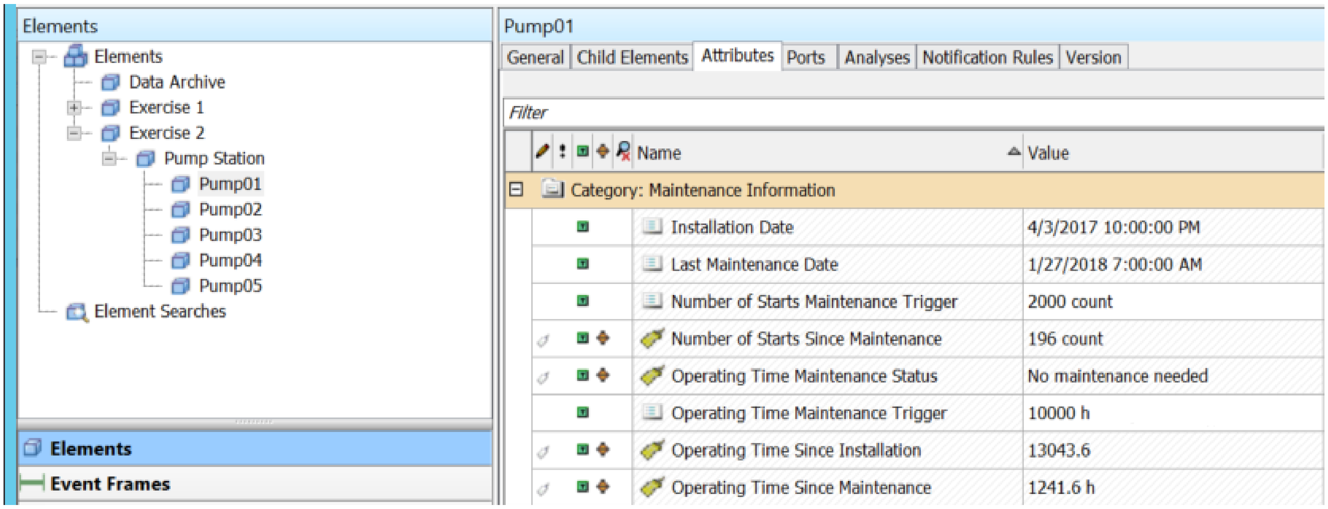


2. From **Elements** section of PI System Explorer, explore the structure for Exercise 2 by drilling-down under **Exercise 2 > Pump Station > Pump01**.

This pump station currently has five (5) pumps. A new sixth pump has been ordered and will soon be installed.

Maintenance is important for these critical assets. Usage-based maintenance has already been implemented, in a manner that we saw for the ice-cream mixers in Exercise 1.

3. From the **Attributes** tab of Pump01, explore the **Maintenance Information** section.



Number of starts and operating time (run hours) thresholds have been added and current totals since the last maintenance can be evaluated to determine if maintenance is required based on those criteria.

4. Explore the analysis expression from the **Analyses** tab. The **Usage-based Calculations** analysis evaluates the new totals on a regular basis and compares them to their limits.

Name	Expression

InstallationRuntime	//Hours since the pump was installed
	//TimeEq function results in seconds; need to define that before converting again to hours
	IF 'Installation Date' > '*' THEN 0
	ELSE Convert(Convert(TimeEq('Pump Status','Installation Date','*',"ON"), "s"), "h")

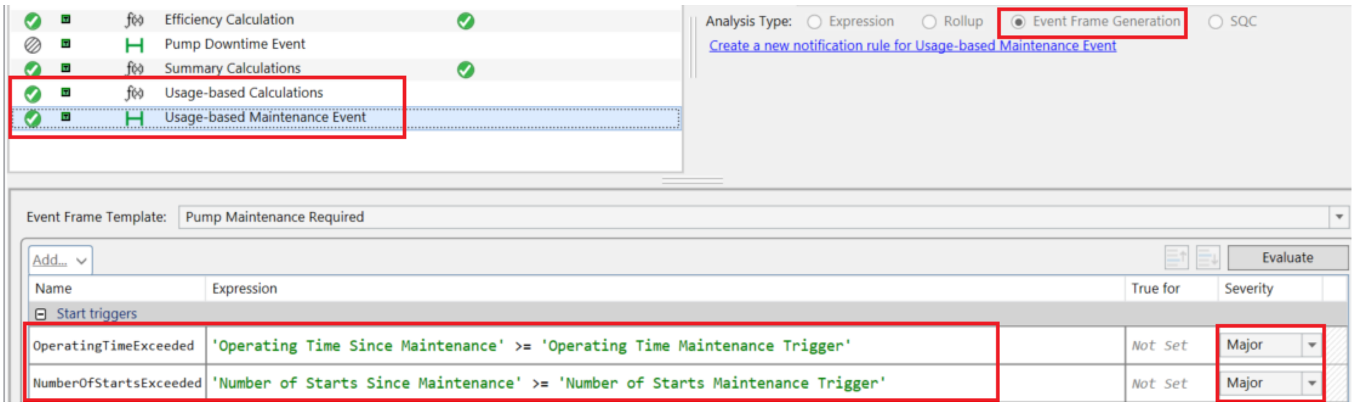
NumberofStarts	//Counts the number of times the value of pump status has changed.
	//Since you have a count for all "on" and "off", divide by 2
	Convert(NumOfChanges('Pump Status','Last Maintenance Date','*')/2, "count")

LastMaintRuntime	//Hours since the last maintenance date
	//TimeEq function results in seconds; need to define that before converting again to hours
	IF 'Last Maintenance Date' > '*' THEN 0
	Else Convert(Convert(TimeEq('Pump Status','Last Maintenance Date','*',"ON"), "s"), "h")

Status	If LastMaintRuntime >= 'Operating Time Maintenance Trigger' Or NumberofStarts >= 'Number of Starts Maintenance Trigger' Then 1 Else 0

In order to keep track of instances where the values violate threshold limits, you can configure analysis to keep track of those as events. Using the **Event Frame Generation** option, events will be generated to track what is relevant to you.

In this example, the usage-based statistics are tracked by the **Usage-based Maintenance Event** analysis.

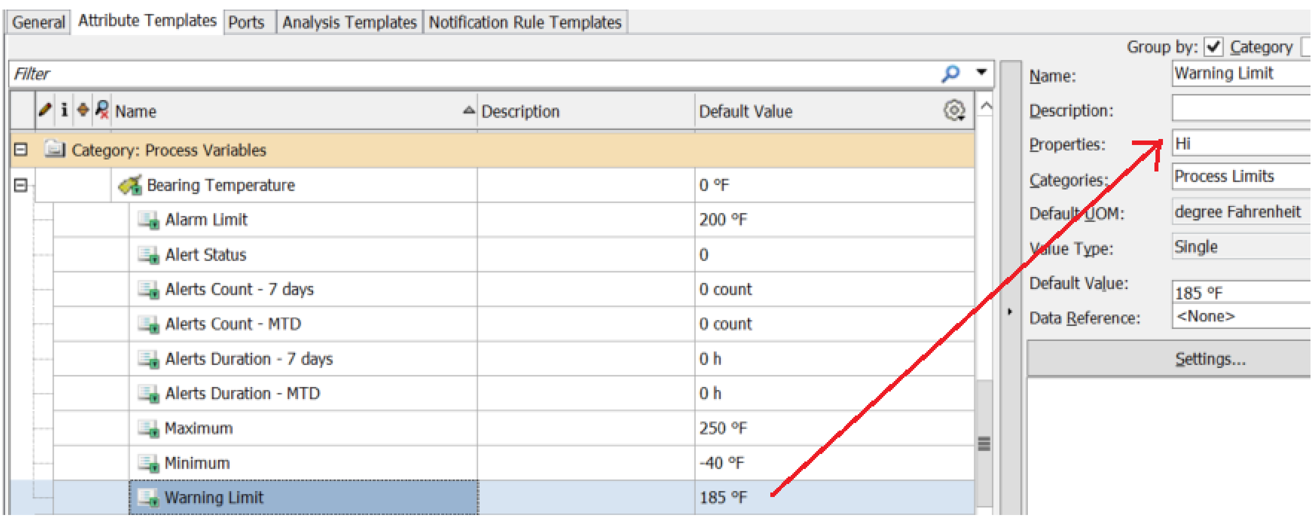


Step 2: Monitoring the bearing temperature

In addition to usage-based metrics, we can also look at sensor data, say, a temperature. Bearing temperatures for the pumps are available.

Under normal conditions, we know that the temperature should not exceed a defined high limit.

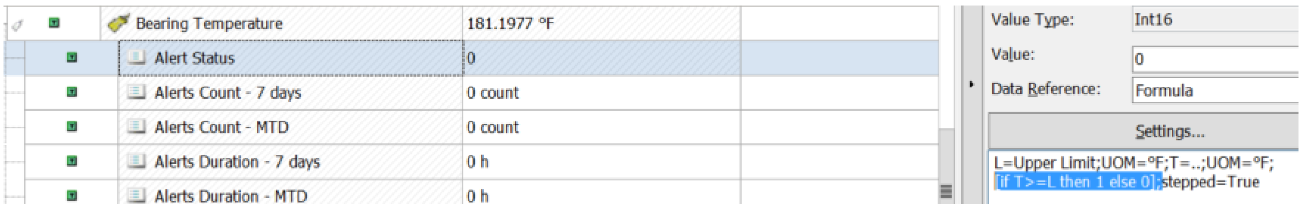
1. Look under the **Attributes** for Pump01 and expand the attributes under the **Bearing Temperature**.



The **Warning Limit** and **Alarm Limit** attributes define the high limits; they are configured with the attribute trait **Hi** and **HiHi** respectively, as shown in the **Properties** field (this will be used in PI Vision).

Note the presence of placeholders for count and duration of temperature alerts; these will be configured in the steps below.

2. Explore the Formula attribute named **Alert Status**. It is evaluating whether or not the bearing temperature is above its warning limit, and if so turns to 1 (if T>=L then 1 else 0). This will be used to count the number of occurrences and the duration of the alerts in the next step.

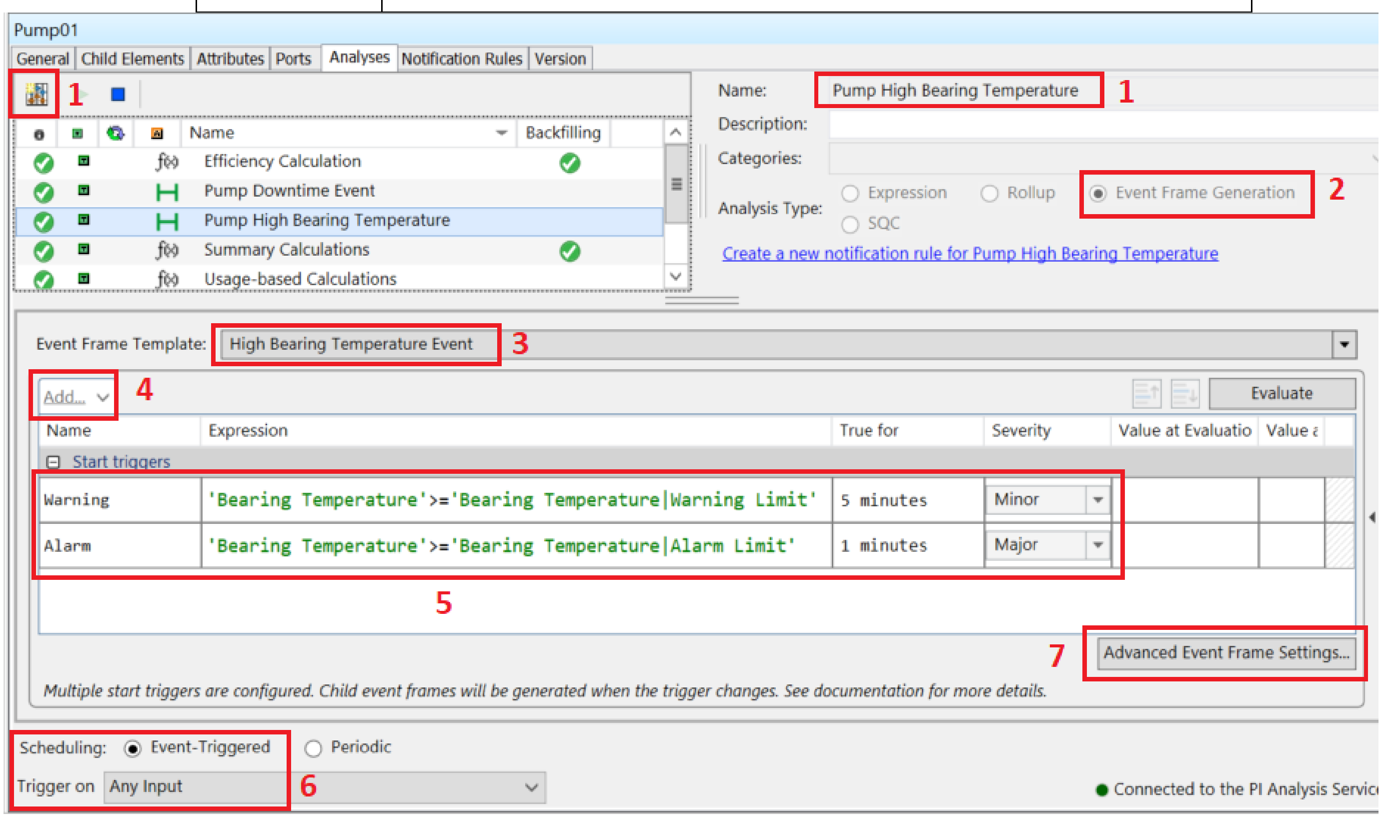


Step 3: Tracking high bearing temperature events

Using Event Frames, we can track the instances where the temperature exceeded its limits.

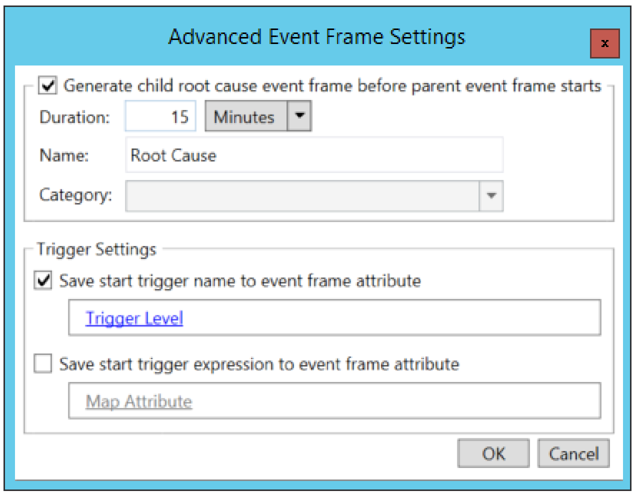
1. Navigate to the **Analyses** tab for Pump01 and create a new analysis named **Pump High Bearing Temperature**.
2. Change the analysis type to **Event Frame Generation**.
3. Select the **High Bearing Temperature Event** event frame template.
4. Add a new **Start Trigger** from the **Add...** link.
5. Configure one Warning-level trigger and one Alarm-level trigger as shown in the below picture.

Name	Expression
Warning	'Bearing Temperature' >= 'Bearing Temperature|Warning Limit'
Alarm	'Bearing Temperature' >= 'Bearing Temperature|Alarm Limit'

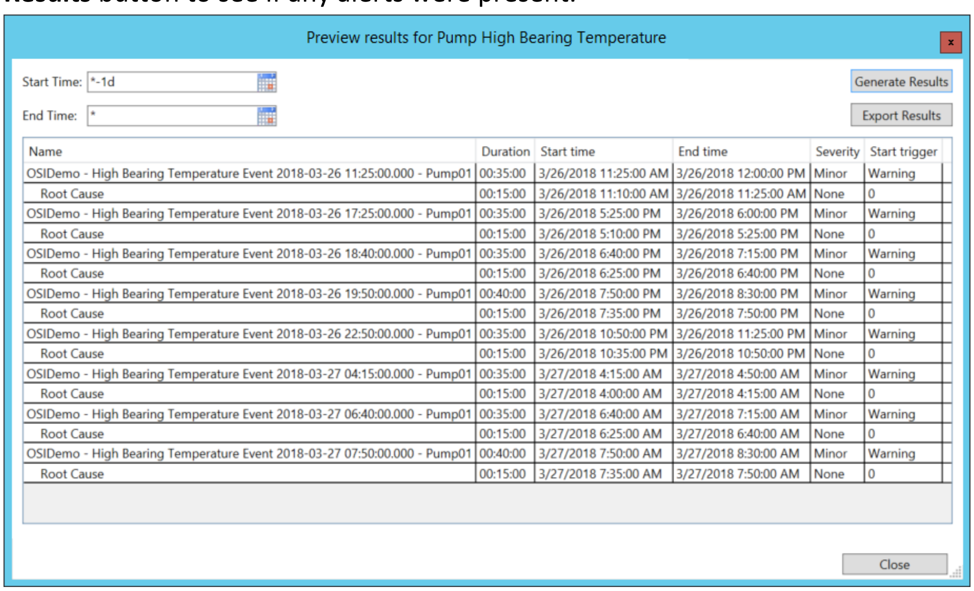


Note: In the current example, the alarm-level trigger needs to be of a higher severity than the warning-level trigger in order to become active. Furthermore, the **True for** (time true) option can be leveraged to make sure valid alerts are being triggered.

6. Leave the scheduling as **Event-Triggered** on **Any Input**.
7. Optionally, you can store the **start trigger name** to an attribute of the event that will get generated from this analysis.
   You can also enable a **Root Cause** child event frame to be generated, in order to have an easy window of time to look at the data (in PI Vision) before the event occurred.



8. Preview the results for Pump01 by right-clicking the **Pump High Bearing Temperature** analysis and selecting **Preview Results**. You can preview the last day (***-1d** to *****) by pressing the **Generate Results** button to see if any alerts were present.

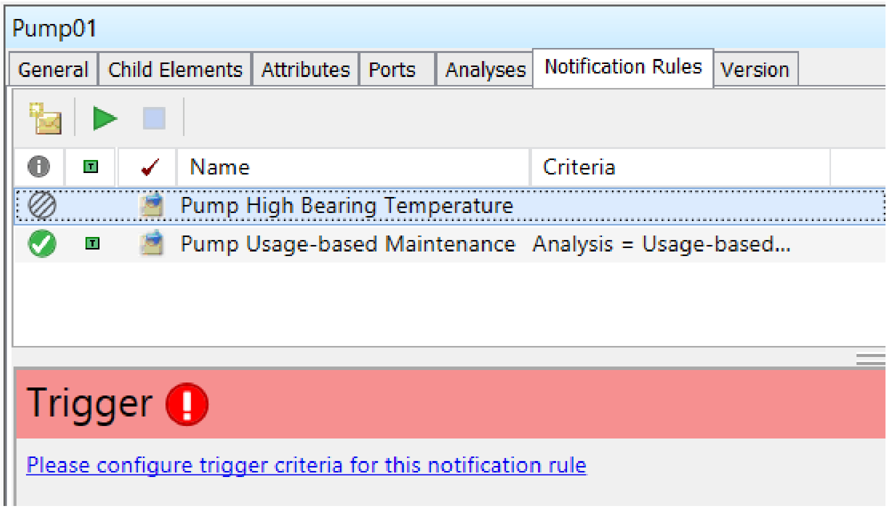


9. Click the **Check In** button from the top toolbar to save the changes, then right-click the Pump High Bearing Temperature analysis and select **Convert to Template** to enable this analysis for all pumps. Click the **Check In** button once more.

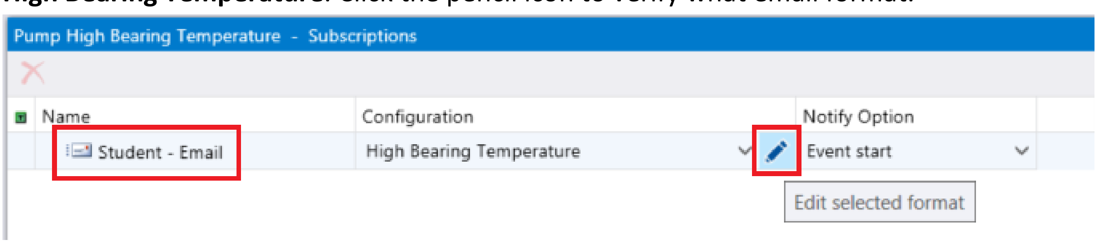
Step 4: Alerting on high bearing temperature events

Events are being tracked by the system, but a Notification can be configured to allow an email to be sent or a web service call to be issued.

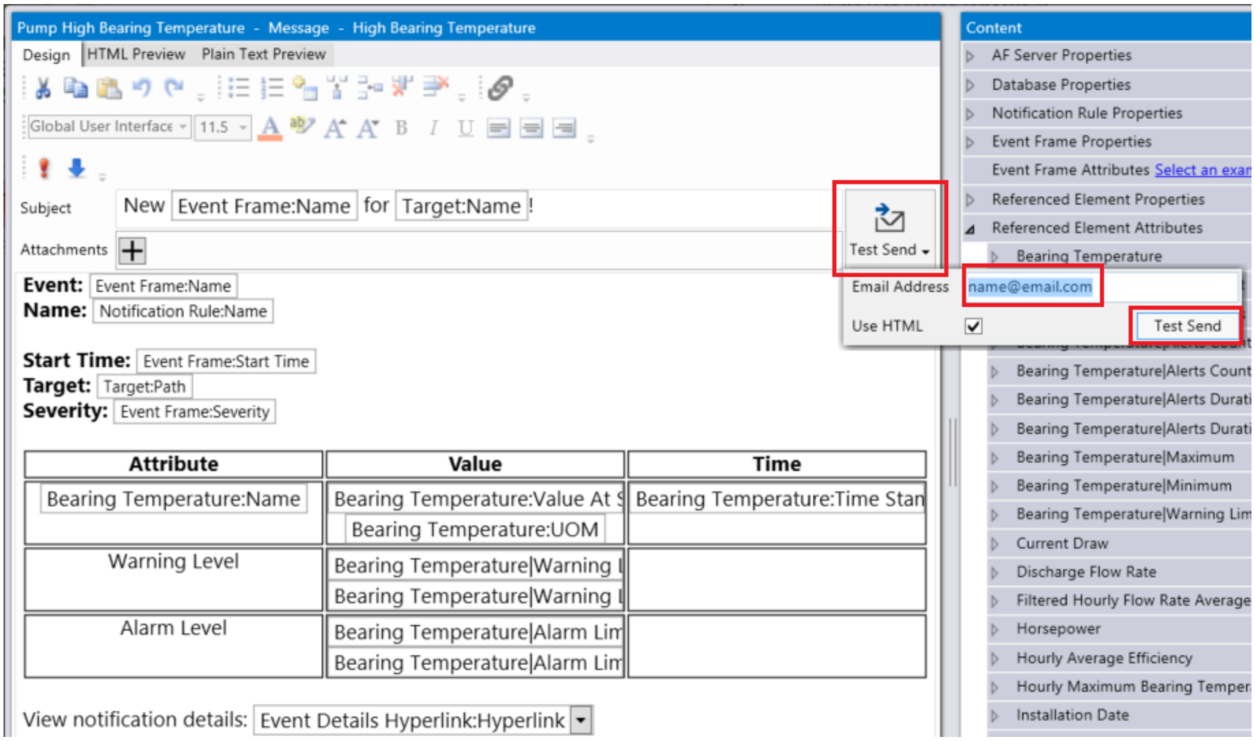
1. Switch to the **Notification Rules** tab of the Pump01 element.
2. Click the **Pump High Bearing Temperature** notification rule.
3. Click the **Please configure trigger criteria for this notification rule** link in the **Trigger** section.



4. Select the **Pump High Bearing Temperature** analysis and leave the rest to default values. Click **OK**.
5. Explore the **Subscriptions** section by clicking the **View/Edit Subscriptions** link on the right.
6. If triggered, the notification will send an email out to the **Student** account, using a format called **High Bearing Temperature**. Click the pencil icon to verify what email format.



7. Before clicking the **Test Send** button, change the email address to student01@pischool.int, which is the email account for your user on this machine.



8. Click **Ok** and **Ok** again to exit the windows.

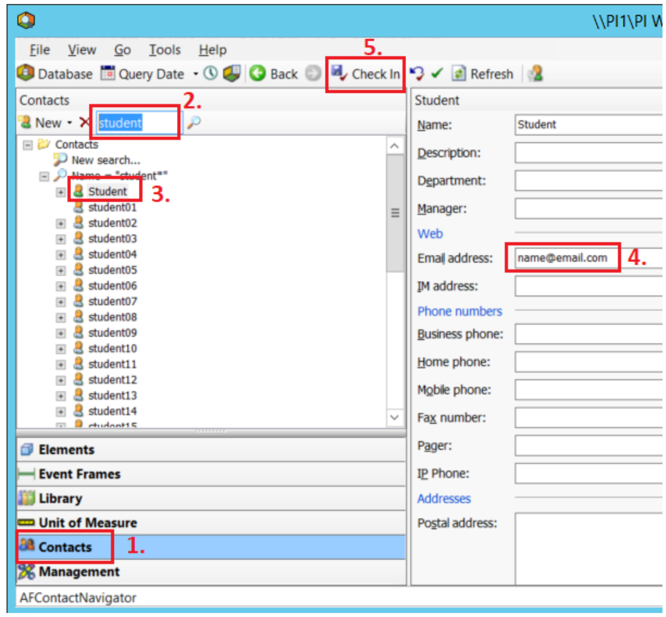
9. Select the **Pump High Bearing Temperature** notification rule and click the **Start** button ( ) to start the rule, and click Check In, then right-click the notification rule to select **Convert to Template** and click Check In again to save the changes.

When a new high bearing temperature event is generated, a notification will be triggered, and an email will be sent out to the student01 account's email address. You can open Outlook to check for these emails.

Step 5: (optional) Sending an email notification on a high bearing temperature alert

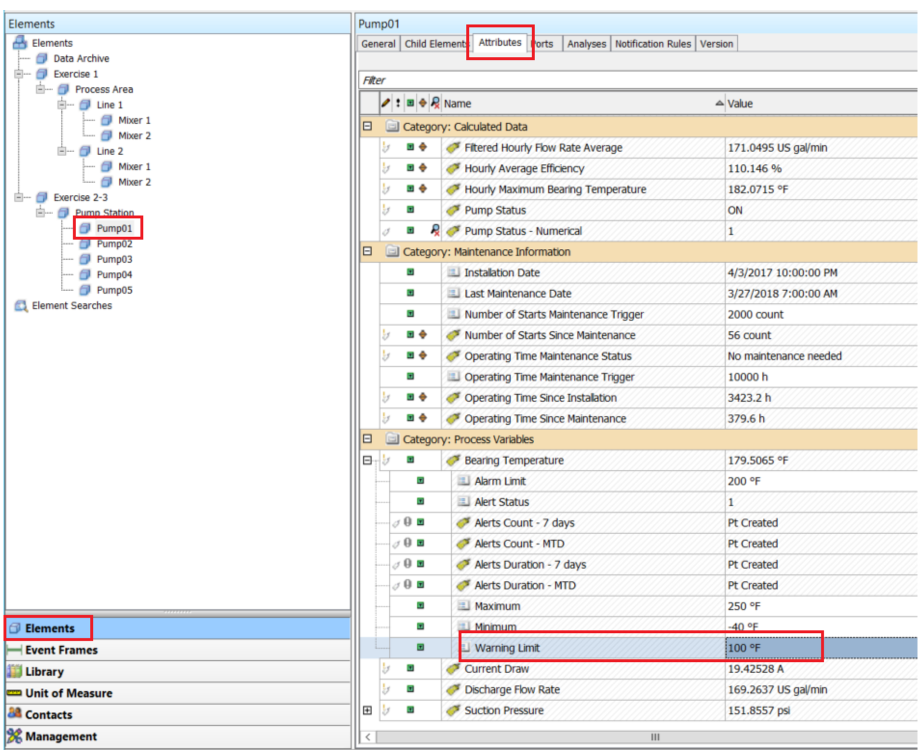
We will first change the email address of the Student to the student01@pischool.int account.

1. From PI System Explorer, navigate to the **Contacts** section (refer to the below picture).
2. Search for **student** in the contact search field.
3. Select the **Student** contact.
4. Modify its **Email address** field to student01@pischool.int .
5. Click the Check In button to save the changes.



The next triggering of the high bearing temperature should send you an email. Instead of waiting, we will force the temperature to be too high.

6. Navigate to the **Elements** section and to the **Exercise 2 > Pump Station > Pump01** element. Select its **Attributes** tab.
7. Expand the **Bearing Temperature** attribute and modify the value of the **Warning Limit** attribute to something lower like **100** °F. Then click the Check In button to save the changes.

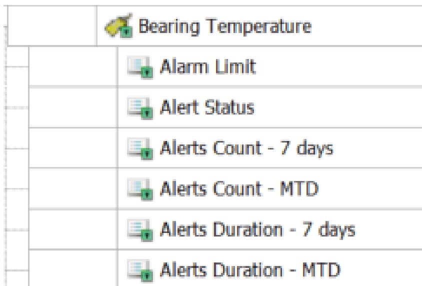


Step 6: Counting number and duration of bearing temperature alerts

For reporting or prioritization purposes, it is useful to have counts on the number of alerts an equipment had over a certain time period.

Total duration of those alerts can also be used to identify equipment most under alert.

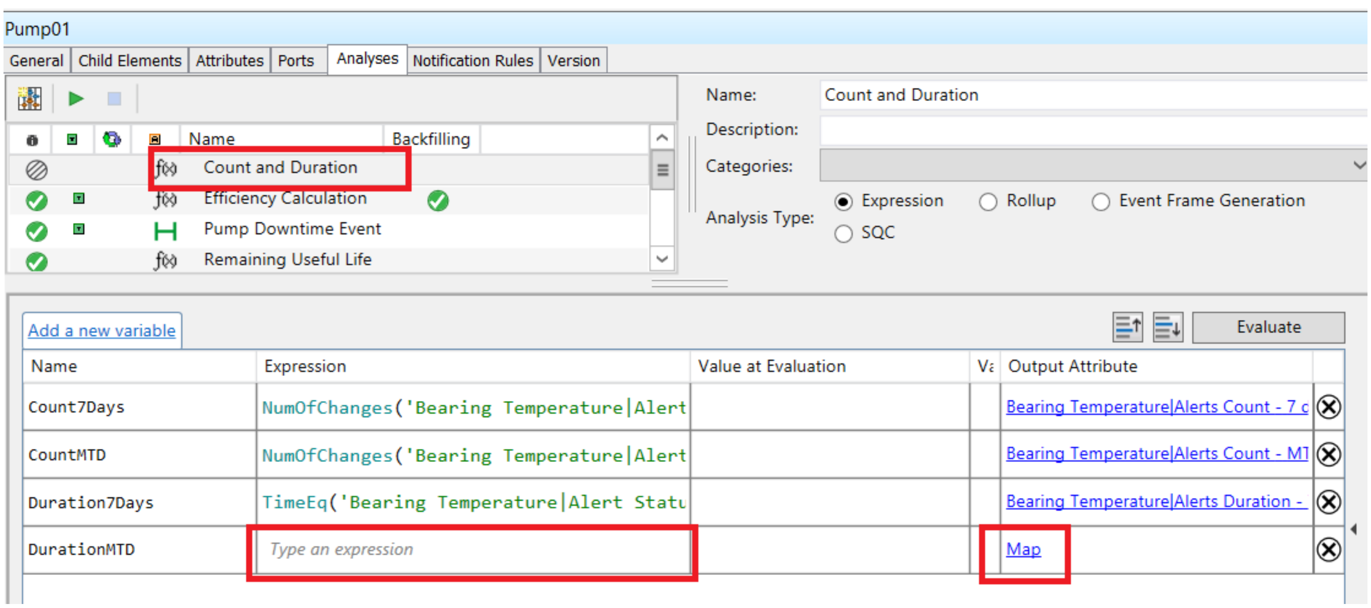
1. We already have placeholders for those counters as part of the **Bearing Temperature** child attributes.



2. Under the **Analyses** tab for **Pump01**, select the **Count and Duration** expression analysis. We only need to complete the fourth variable and start the analysis.
3. Use the **TimeEq()** function to do so on the **Alert Status** attribute to calculate the total duration the bearing temperature was in alert since the beginning of the month.

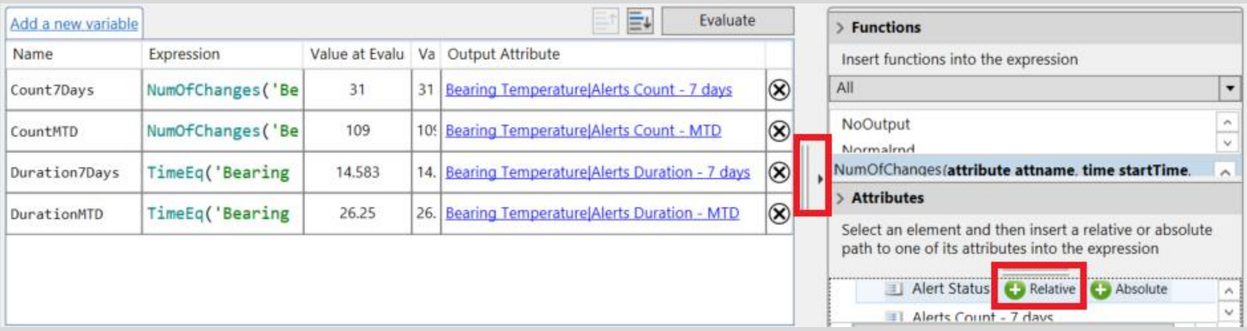
Name	Expression
DurationMTD	`TimeEq('Bearing Temperature|Alert Status','1','*',1)/3600`

4. **Map** the output to the right bearing temperature children attribute.



5. The scheduling is Periodic (5 minutes).
6. Click **Evaluate** to confirm the calculations are functioning properly.

Note: When writing an expression, the auto-complete feature will not suggest child attributes. They can be added from the right-hand side panel:



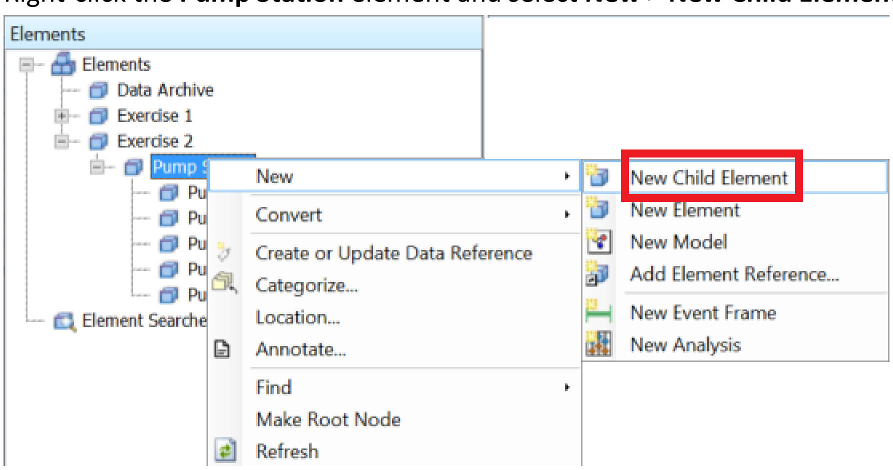
It can also be added by typing the attribute name **'Bearing Temperature|Alert Status'** directly in the expression field.

7. Click Check In, then the **Start** button ( ) to start the analysis, then right-click the analysis to select **Convert to Template** and click Check In again to save the changes.

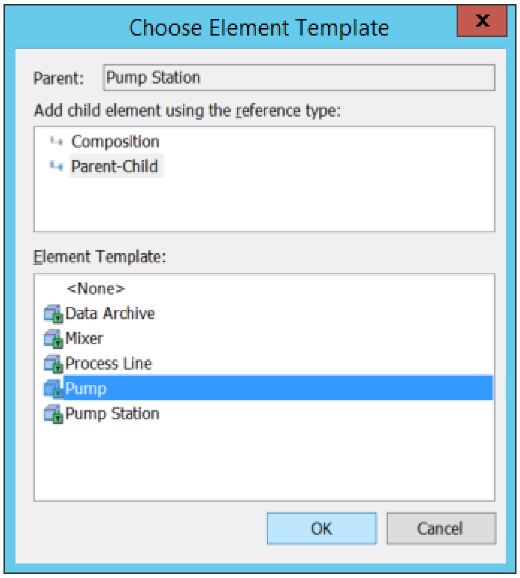
Step 7: (Optional) Adding Pump06

In the current example, we have a Pump template. It includes the attributes, the analyses and notification rules. Pump06 was recently added to the Pump Station and we need to add it to asset structure.

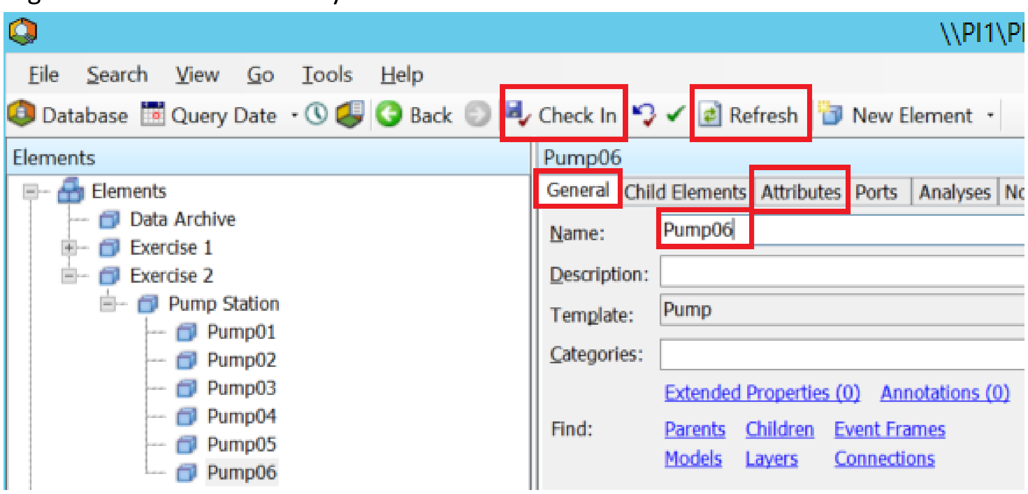
1. Right-click the **Pump Station** element and select **New > New Child Element**.



2. Select the **Pump** template and click **OK**.



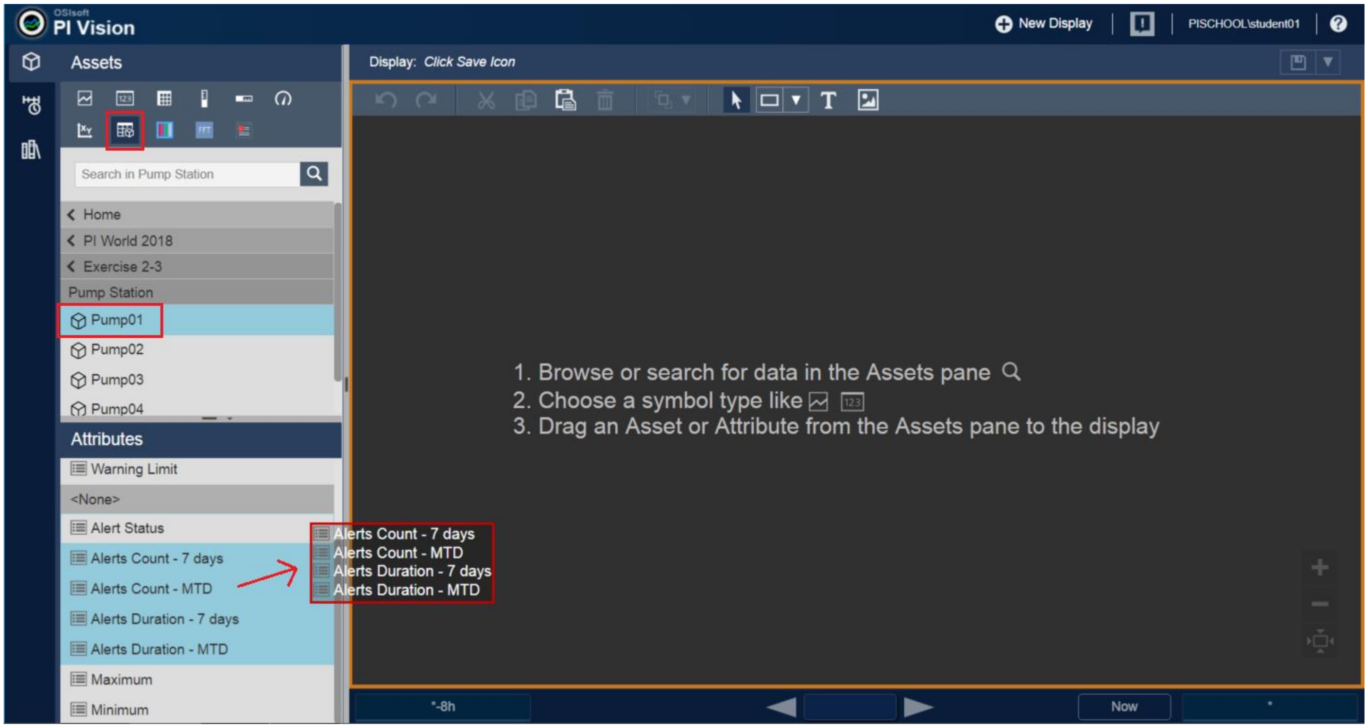
3. Under the **General** tab of the newly created element, rename the element to **Pump06**.
4. Switch to the **Attributes** tab and click the Check In button, and then the **Refresh** button. The tags are found and the analyses started.



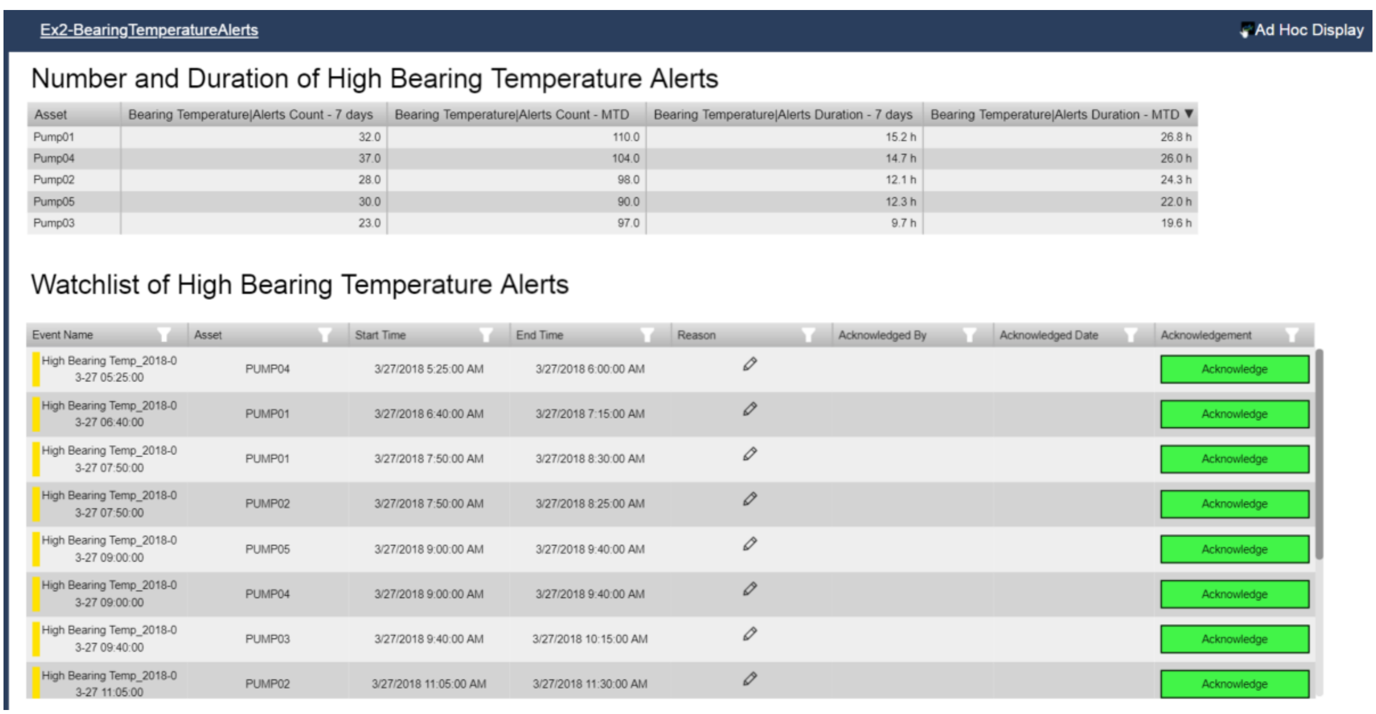
Step 8: (Optional) Visualizing counts and watchlist of events

An easy way to share this information is via PI Vision. Use the below steps to build a new display, or use the existing completed display (https://pi1.pischool.int/PIVision/#/Displays/118/Ex2-BearingTemperatureAlerts).

1. Open the **Google Chrome** web browser from the taskbar and click the **PI Vision** link from the bookmark tool bar or navigate to https://pi1.pischool.int/PIVision.
2. Click the **+ New Display** button in the upper right of the page to create a new display.
3. Use the Assets pane on the left hand side to reach PI World > Exercise 2 > Pump Station > **Pump01**.
4. Select the Asset Comparison Table symbol ( ).
5. Drill-down under the Bearing Temperature attribute from the Attributes section at the bottom.
6. Using the Ctrl or Shift key on your keyboard to multi-select, drag-and-drop the 7-days and MTD count and duration attributes located under the Bearing Temperature attribute.

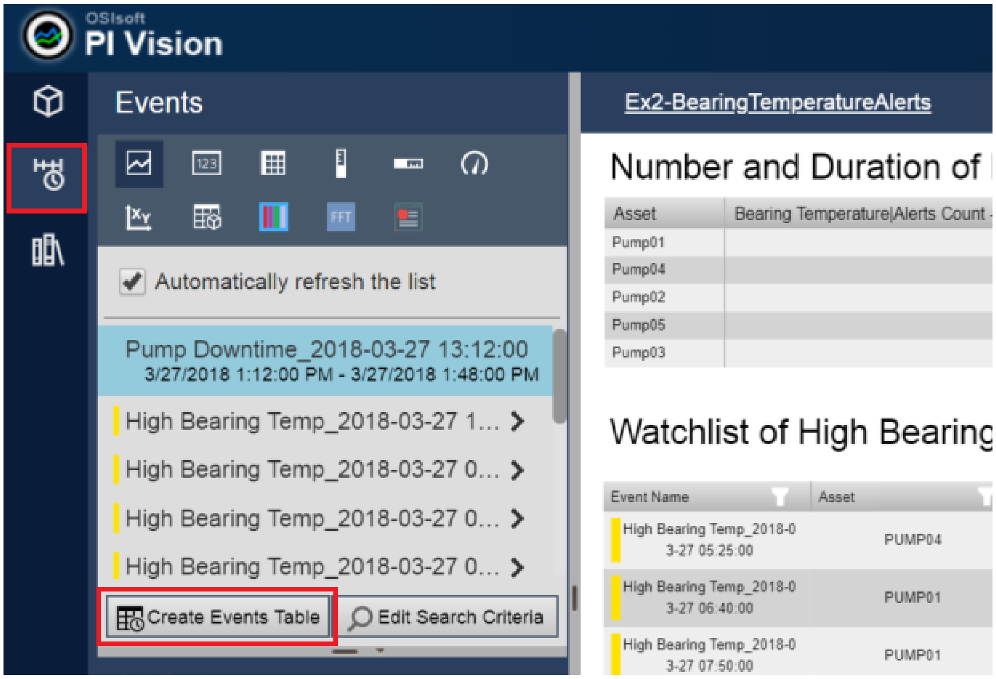


7. Once you have the proper attributes added for Pump01, drag-and-drop the other pumps elements on the asset comparison table to add extra rows for those other pumps.
8. You can now order the pumps by their MTD hours in alert to understand which asset most under alert condition; in the below example it is Pump01.

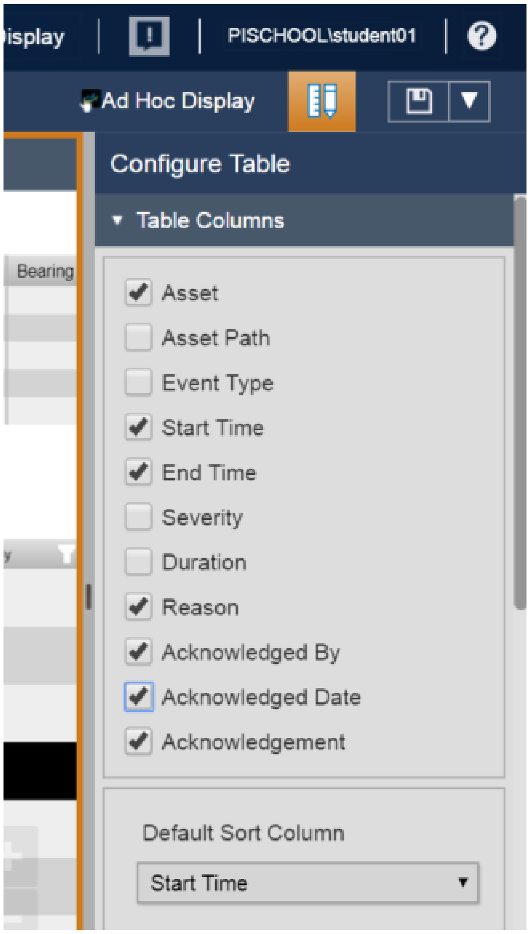


Note: You can change the PI Vision display background color by right-clicking the background and selecting **Format Display**.

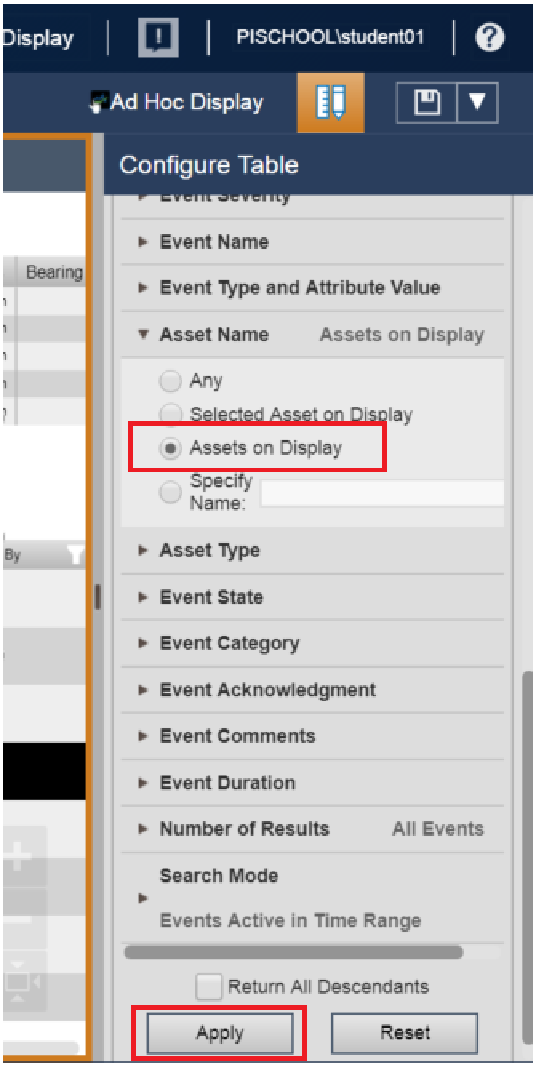
9. Open the left-hand side **Events** pane and click the **Create Events Table** button to add a table that can be used as a watchlist of recent high bearing temperature alerts.



10. Right-click the Events Table to select **Configure Table**.
11. From the configuration pane that shows up, check to add the **Reason**, **Acknowledged By**, and **Acknowledged Date** columns.



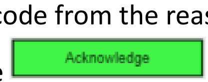
12. Make sure the **Asset Name** field has the **Assets on Display** radio button selected.
13. Click the **Apply** button at the bottom to confirm the changes.



14. Resize the table so it shows all columns correctly.

Step 9: (Optional) Acknowledging and entering reason code for the alerts

The bottom events table shows the active high bearing temperature events in the time range, defined by the display time-bar at the bottom of the screen. The configuration of those events allows you to acknowledge it, as well as to enter a reason code. Both functionalities can be performed from the event table symbol. Acknowledging is useful when sending Notifications, where you need to confirm that they are aware of the alert. The reason code value can leverage a reason tree to specify the cause of the alert, if available.

1. Select one recent event and enter a reason code by clicking the  button and selecting a reason code from the reason tree.
2. Click the 

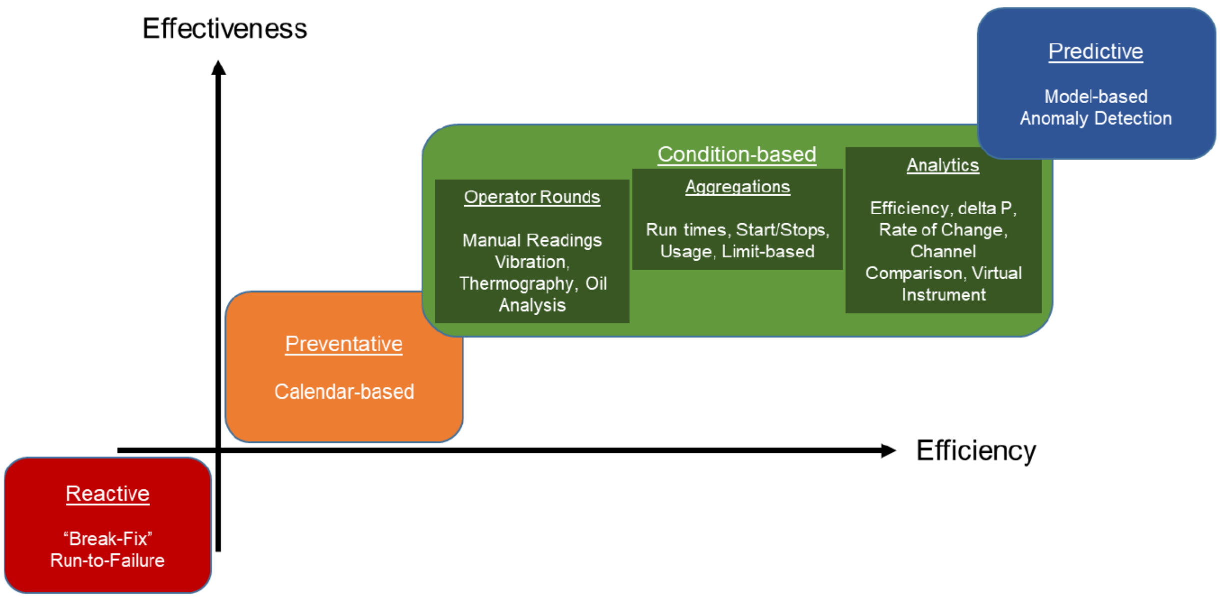
button and confirm you can see your username and acknowledgement time after you clicked it.

Event Name	Asset	Start Time	End Time	Reason	Acknowledged By	Acknowledged Date	Acknowledgement
High Bearing Temp_2018-0 3-27 06:40:00	PUMP01	3/27/2018 6:40:00 AM	3/27/2018 7:15:00 AM	Reason4	PISCHOOL\student01	3/27/2018 2:18:11 PM	Acknowledged

Exercise 3a – Predictive Maintenance (PdM) – Bearing Vibration

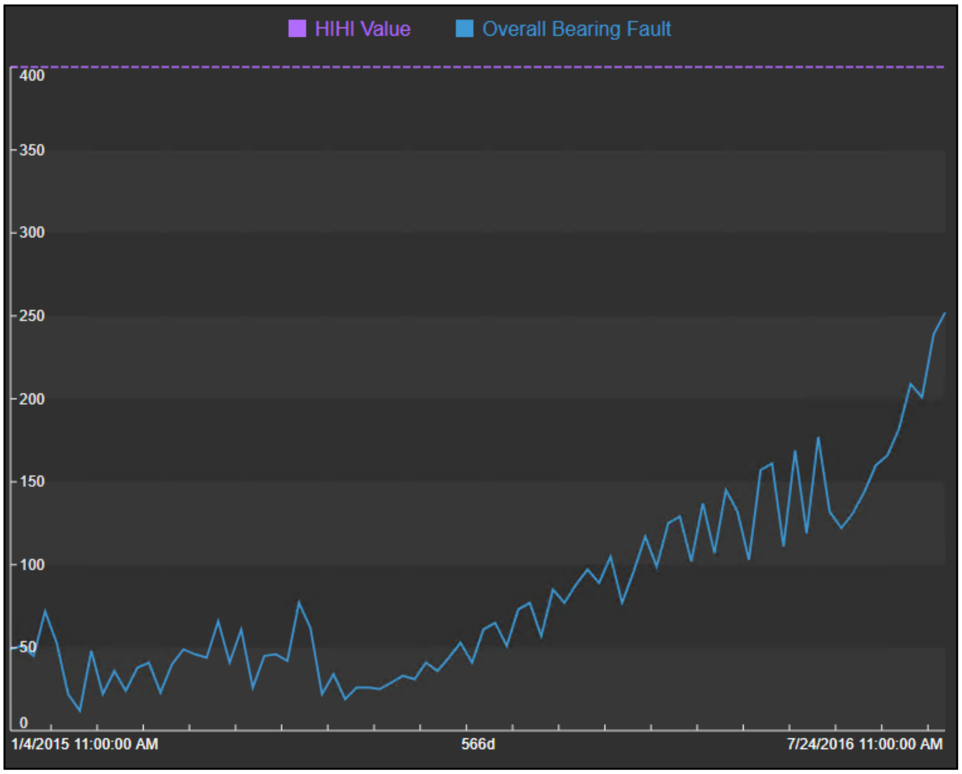
In an equipment/asset maintenance and reliability context, the layers of analytics can be viewed as:

- ***Usage-based Maintenance***
- ***Condition-based Maintenance***
- ***Predictive Maintenance - AF (simple predictive) and third-party libraries (advanced predictive)***

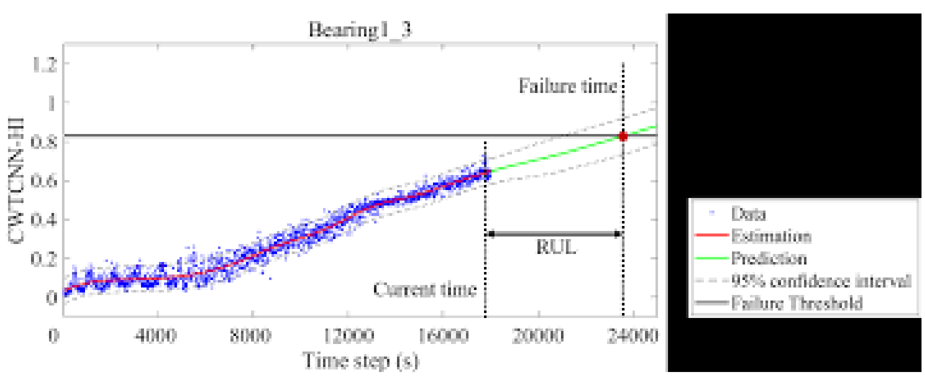


Here, we illustrate PdM (predictive maintenance – simple analytics) using vibration data for a pump to predict its remaining useful life (RUL). The following method uses built-in AF Asset Analytics function.

The vibration data represents the nominal percent (of normal) vibration over a period of 82 weeks; a new value is collected every week. The vibration values increase over time as shown below:



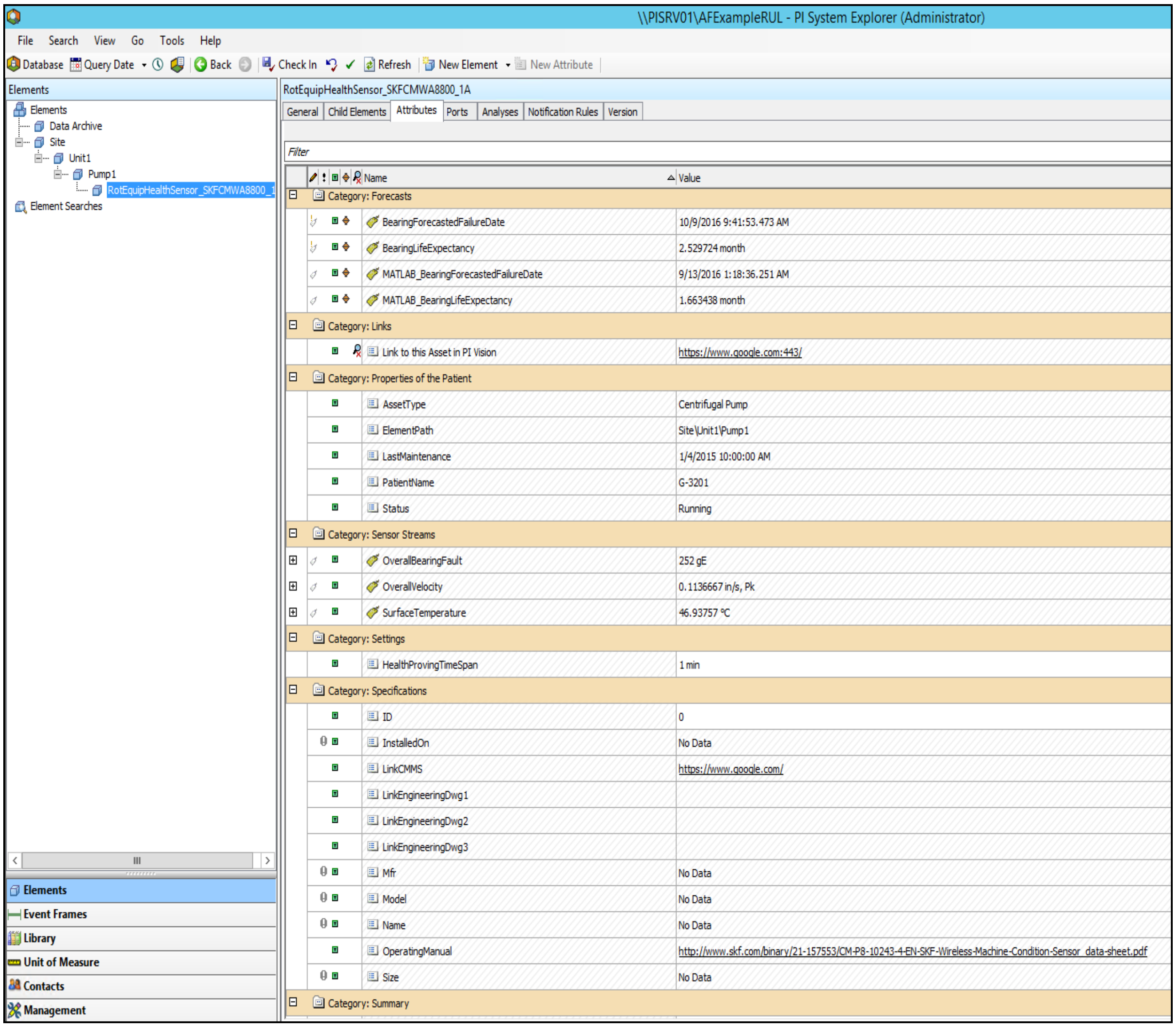
We will calculate the estimated RUL till we reach the HIHI value of 400. The calculations return the failure time represented in the trend below by using linear extrapolation.



## Step 1:	Examine the Data

Let's first look at the AF structure:

1. Open PI System Explorer
2. On the top left corner, click on Database, and then double click "AFExampleRUL"
3. Expand Site > Unit 1 > Pump 1 > RotEquipHealthSensor_SKFCMWA8800_1A
4. Click on the above asset and then click the Attributes Tab to examine it



5. Expand the "OverallBearingFault" attribute and check its child attributes

Category: Sensor Streams	
OverallBearingFault	252 gE
b	185.44 gE
Hi	300 gE
HiHi	400 gE
LinearRegression Event Count	12
m	0.76349 gE/day
Maximum	500 gE
MovingAverage	225.25
MovingAverage Event Count	4
NumEvents	82 count
PctGoodData	99.993 %
r_squared	0.64878

6. Below are some important attributes we'll be dealing with as part of the RUL calculation:
    a. **OverallBearingFault**: the vibration nominal value. We have 82 values for this attribute, values update every week, and will range from 49 to 252 over a period of 82 weeks
    b. **OverallBearingFault|HIHI**: this is the HIHI value for the vibration; we need to calculate the RUL till we reach this HIHI value
    c. **OverallBearingFault|MovingAverage**: this will store the moving average values of the vibration data. The linear fit will be done on the moving average values, as opposed to the actual vibration values.
    d. **OverallBearingFault|MovingAverage Event Count**: this sets the number of events in the MovingAverage calculation above.
    e. **OverallBearingFault|LinearRegression Event Count**: this sets the number of events in the Linear Regression calculation that will output the value for m and b.
    f. **OverallBearingFault|b**: this will store the intercept of the line being generated from the moving linear regression calculation we will implement in AF Analytics on the moving average values
    g. **OverallBearingFault|m**: this will store the slope of the line being generated from the moving linear regression calculation we will implement in AF Analytics on the moving average values
    h. **OverallBearingFault|r_squared**: this will store the $\mathbf{r^2}$ of the line being generated from the moving linear regression calculation we will implement in AF Analytics on the moving average values. The closer $\mathbf{r^2}$ is to 1, the better the fit
    i. **BearingLifeExpectancy**: the calculated RUL in days till we reach the HIHI value. This will be calculated using a moving built-in linear regression function in PI Asset Analytics
    j. **BearingForecastedFailureDate**: the predicted failure date based on the BearingLifeExpectancy calculation

Step 2: Examine the moving average linear regression calculations in AF Analytics for calculating the RUL

In this section, we will examine AF Analytics where we calculate the RUL based on a moving linear regression algorithm. This is implemented because when observing the data, you can clearly see that the curve has different slopes at different times.

1. Open PI System Explorer
2. On the top left corner, click on Database, and then double click “AFExampleRUL”
3. Expand Site > Unit 1 > Pump 1, and click on “RotEquipHealthSensor_SKFCMWA8800_1A”
4. Click the “Analyses” tab on the right
5. Check the “Bearing Life Calculations” analysis
6. The formulas of the “Bearing Life Calculations” analysis which relate to this section are shown below:

<table>
<tr><th>Name</th><th>Expression</th><th>Va</th><th>Va</th><th>Output Attribute</th></tr>
<tr><td>MovingAverageEvents</td><td>RecordedValuesByCount('OverallBearingFault','*','OverallBearingFault|MovingAverage Event Count')</td><td></td><td></td><td>Map</td></tr>
<tr><td>MovingAverage</td><td>If ArrayLength(MovingAverageEvents)='OverallBearingFault|MovingAverage Event Count'
Then Avg(MovingAverageEvents) Else NoOutput()</td><td></td><td></td><td>OverallBearingFault|MovingAverage</td></tr>
<tr><td>LinearRegressionEvents</td><td>RecordedValuesByCount('OverallBearingFault|MovingAverage','*','OverallBearingFault|LinearRegression Event Count')</td><td></td><td></td><td>Map</td></tr>
<tr><td>LinearRegressionEventsTimestamp</td><td>TimeStamp(LinearRegressionEvents)</td><td></td><td></td><td>Map</td></tr>
<tr><td>LinearRegressionEventsStartTime</td><td>FirstValue(LinearRegressionEventsTimestamp)</td><td></td><td></td><td>Map</td></tr>
<tr><td>LinearRegressionEventsEndTime</td><td>LastValue(LinearRegressionEventsTimestamp)</td><td></td><td></td><td>Map</td></tr>
<tr><td>LinearRegr</td><td>LinRegr('OverallBearingFault|MovingAverage', LinearRegressionEventsStartTime, LinearRegressionEventsEndTime,50)</td><td></td><td></td><td>Map</td></tr>
<tr><td>Fit</td><td>If BadVal(LinearRegr) Then NoOutput() Else LinearRegr</td><td></td><td></td><td>Map</td></tr>
<tr><td>EnableFit</td><td>ArrayLength(LinearRegressionEvents)='OverallBearingFault|LinearRegression Event Count'</td><td></td><td></td><td>Map</td></tr>
<tr><td>m</td><td>If Not(BadVal(LinearRegr)) And EnableFit Then Convert(Fit[1]*24*3600, "gE/day") Else NoOutput()</td><td></td><td></td><td>OverallBearingFault|m</td></tr>
<tr><td>b</td><td>If Not(BadVal(LinearRegr)) And EnableFit Then Convert(Fit[2], "gE") Else NoOutput()</td><td></td><td></td><td>OverallBearingFault|b</td></tr>
<tr><td>rsquared</td><td>If Not(BadVal(LinearRegr)) And EnableFit Then Convert(Fit[3],"ratio") Else NoOutput()</td><td></td><td></td><td>OverallBearingFault|r squared</td></tr>
<tr><td>LifeExpectancy</td><td>If Not(BadVal(LinearRegr)) And EnableFit And m>0 And rsquared>.400
Then Convert(('OverallBearingFault|HiHi'-b)/m, "h") Else NoOutput()</td><td></td><td></td><td>BearingLifeExpectancy</td></tr>
<tr><td>ForecastedFailDate</td><td>If Not(BadVal(LinearRegr)) And EnableFit And m>0 And rsquared>.400
Then TimeStamp('OverallBearingFault') + LifeExpectancy*60*60 Else NoOutput()</td><td></td><td></td><td>BearingForecastedFailureDate</td></tr>
</table>

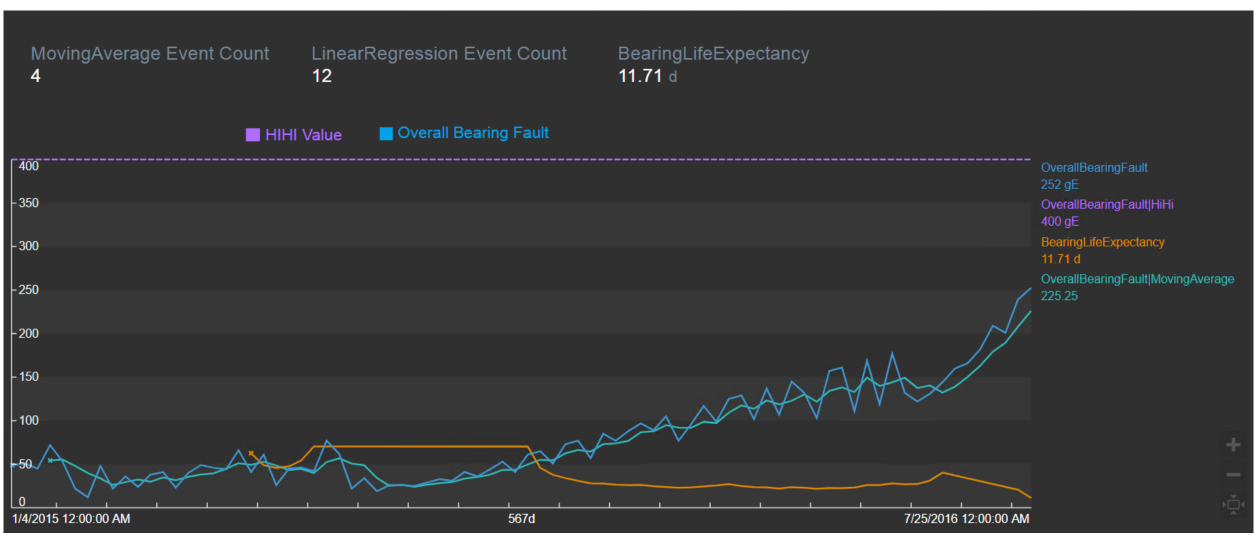
7. Below is a brief description of each formula:
    a. **MovingAverageEvents:** Returns an array of the values the length of which is specified by the MovingAverage Event Count attribute
    b. **MovingAverage:** Calculates an average of all the values from the previous array
    c. **LinearRegressionEvents:** Returns an array of the values the length of which is specified by the LinearRegression Event Count attribute
    d. **LinearRegressionEventsTimestamp:** Returns the timestamps of all the values in the previous array
    e. **LinearRegressionEventsStartTime:** Extracts the first timestamp from the array to be used in the LinRegr function
    f. **LinearRegressionEventsEndTime:** Extracts the last timestamp from the array to be used in the LinRegr function
    g. **LinearRegr**: performs a linear regression on the past 12 moving average values, and returns and array of 3 values; the slope of the line, the intercept, and the $\mathbf{r^2}$

h. **Fit**: stores the array value from the previous formula assuming no errors were generated
i. **Enable Fit**: Checks that the previously specified number of events exist for the Linear Regression before proceeding
j. **m**: extracts the slope of the line generated from the array result of the **LinearRegr** formula
k. **b**: extracts the intercept of the line generated from the array result of the **LinearRegr** formula
l. **rsquared**: extracts the $\mathbf{r^2}$ value of the line generated from the array result of the **LinearRegr** formula
m. **LifeExpectancy**: calculates the RUL till we reach the HIHI value of 400, based on the slope, the intercept, and the time of the calculation. The $\mathbf{r^2}$ is checked to make sure its value is not too low, which might result in an unreliable RUL prediction. The prediction is converted to hours and mapped to the **BearingLifeExpectancy** attribute, which is set to convert hours to days in the attribute template
n. **ForecastedFailDate**: uses the calculated **LifeExpectancy** and the calculation time to determine the estimated fail date

Step 3: Simulating the calculations

In this section, we will simulate receiving the vibration data over a period of 82 weeks and examine the results of the RUL calculations.

1. Navigate to the Desktop and click on the “PI Vision” Shortcut
2. Use the tree menu on the left to navigate to the “Vibration RUL” displays
3. Click on the “Vibrations RUL” display
4. This Display shows us the important information from the analytics. Here the user can quickly see the methods used and RUL.



Exercise 3b – Engine failure - CM, PM and PdM - early fault detection via machine learning

This is a "discussion only" Exercise to explore the questions below. The machine learning – predictive model development, model deployment etc. is covered in a separate lab.

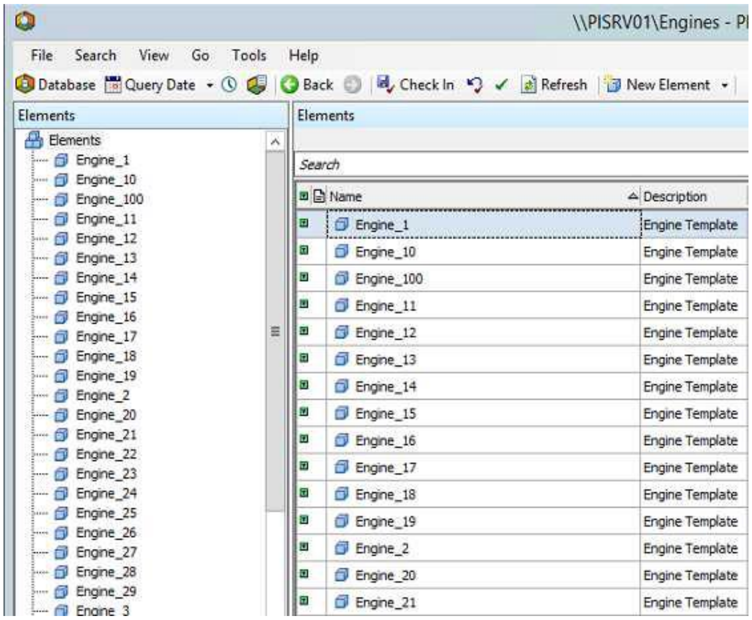
In this Exercise, we use engine operations data and failure history to guide maintenance decisions, and quantify the benefits in moving from CM to PM to PdM:

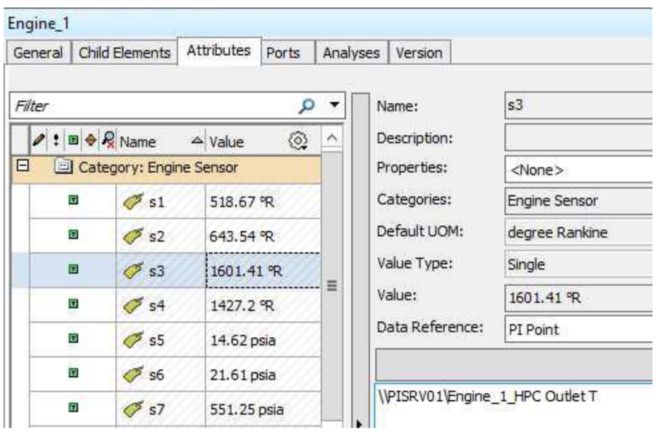
- Corrective maintenance - break-fix
- Preventive maintenance - run-hours based
- Predictive maintenance - early detection (via machine learning - multi-variate condition assessment)

In a deployment with about 100 similar engines, sensor data such as rpm, burner fuel/air ratio, pressure at fan inlet, and twenty other measurements plus settings for each engine – for a total of about 2000 tags – are available. On average, an engine fails after 206 cycles, but it varies widely - from about 130 to 360 cycles – each cycle is about one hour.

The engine data – for the 100 engines is as below.

The engine AF database is available in a separate VM – and is out of scope for the current discussion.


\\PISRV01\Engines - PI
File Search View Go Tools Help
Database Query Date Back Check In Refresh New Element
Elements
Search
Name
Description
Engine_1
Engine Template


Engine_1
General
Child Elements
Attributes
Ports
Analyses
Version
Filter
Category: Engine Sensor
s1 518.67 °R
s2 643.54 °R
s3 1601.41 °R
s4 1427.2 °R
s5 14.62 psia
s6 21.61 psia
s7 551.25 psia
Name: s3
Description:
Properties: <None>
Categories: Engine Sensor
Default UOM: degree Rankine
Value Type: Single
Value: 1601.41 °R
Data Reference: PI Point
\\PISRV01\Engine_1_HPC Outlet T

Category: Engine Sensor	
s1	518.67 °R
s2	643.54 °R
s3	1601.41 °R
s4	1427.2 °R
s5	14.62 psia
s6	21.61 psia
s7	551.25 psia
s8	2388.32 rpm
s9	9033.22 rpm
s10	1.3
s11	48.25
s12	520.08
s13	2388.32 rpm
s14	8110.93 rpm
s15	8.5113
s16	0.03
s17	396
s18	2388
s19	100
s20	38.48
s21	22.9649
Category: Engine Setting	
setting1	0.0009
setting2	0
setting3	100
Category: Engine Status	
Runtime	0
Status	Stopped

Note that the historical sensor data is not relevant to the CM/PM/PdM questions in the sections below – but is shown here for informational purpose only.

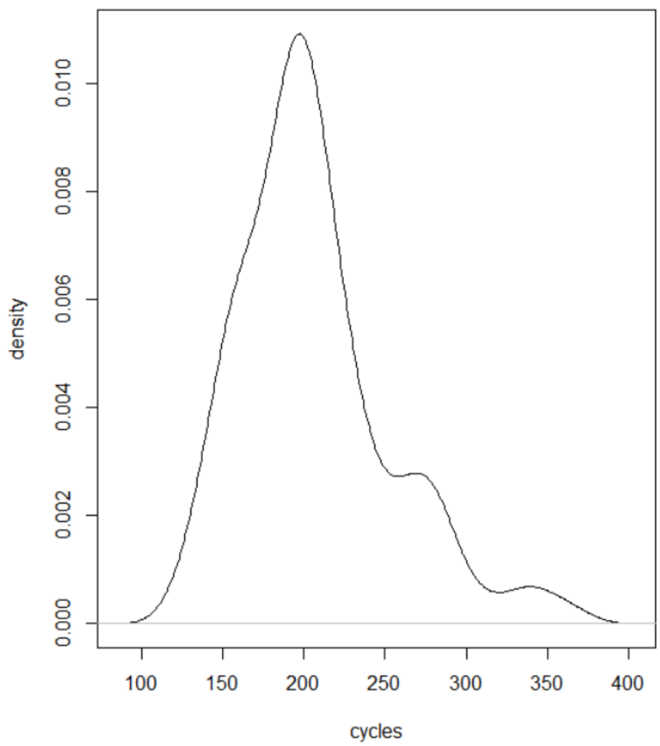
Step 1: Failure History

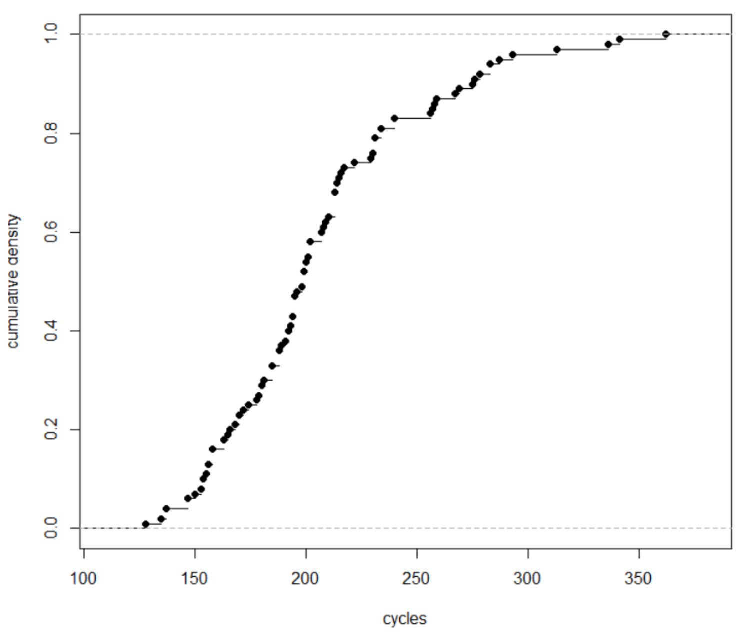
For the 100 engines, the failure history i.e. the number of runs or cycles when an engine fails is shown below. Also, shown are the density and cumulative density plots. Note that the engine failures are reasonably normally distributed – mean is 206 cycles, median is 199, minimum is 128 and maximum is 362.

	A	B	C
1	EngineID	cycle number	
2	1	192	
3	2	287	
4	3	179	
5	4	189	
6	5	269	
7	6	188	
8	7	259	
9	8	150	
10	9	201	
11	10	222	
12	11	240	
13	12	170	
95	94	258	
96	95	283	
97	96	336	
98	97	202	
99	98	156	
100	99	185	
101	100	200	
102	Sum	20631	
103	Average	206.31	
104	Median	199	
105	Min	128	
106	Max	362	
107			

The full failure history is as below - in 5 rows, 20 engines per row, showing the cycle number when the engine failed:

192	287	179	189	269	188	259	150	201	222	240	170	163	180	207	209	276	195	158	234
195	202	168	147	230	199	156	165	163	194	234	191	200	195	181	158	170	194	128	188
216	196	207	192	158	256	214	231	215	198	213	213	195	257	193	275	137	147	231	172
185	180	174	283	153	202	313	199	362	137	208	213	213	166	229	210	154	231	199	185
240	214	293	267	188	278	178	213	217	154	135	341	155	258	283	336	202	156	185	200


density
0.000
0.002
0.004
0.006
0.008
0.010
100
150
200
250
300
350
400
cycles


cumulative density
0.0
0.2
0.4
0.6
0.8
1.0
100
150
200
250
300
350
cycles

Step 2: Corrective, preventive and predictive maintenance

In addition to the failure history, the following cost data is available.

- Each engine run (lasts an hour) and adds $1000 to profit
- Each engine PM costs $10,000 and takes 10 hours
- A failed engine costs $20,000 to repair and takes 20 hours

Currently, maintenance uses a break/fix philosophy i.e. wait for an engine to fail before doing any maintenance.

- Can you quantify the $ spent on maintenance with the break-fix strategy (corrective maintenance)?
- A sister company with similar operations, failure history and repair/PM costs uses the median failure rate of 199 cycles for PMs. Should you adopt this?
- Can you do better? If so, after how many cycles will you do the PMs?
- Can you quantify the benefits in moving from corrective to run-hours based PMs?

Lastly, in considering predictive maintenance (PdM) i.e. data science/machine learning etc., the maintenance department has informed us that they need 20 hours (cycles) notice to schedule the PMs.

As such consider the following:

- If engine operations data can be used for early detection of failure – say, within 20 cycles of a failure with 100% accuracy – if and how much will you save by using PdM vs the PM approach

Re. how to interpret "within NN cycles", there is uncertainty in predicting when an engine will fail – and the more I'm willing to give away, the more certain that I'll be correct.

"Within 20 cycles" says that it could fail in the next cycle or in the next 10th or the next 15th cycle etc. – but based on the failure history, I know with 100% certainty that it will fail in the next 20 cycles – and I'm 100% sure that I'm not giving away more than 20 cycles.

Regarding simulation-based approach to answer some of the above questions, see https://turbofan.fastforwardlabs.com - this uses the same engine failure operations and failure data – but with a different cost structure for PMs and repairs.

Regarding early failure detection (within 20 cycles), the machine learning based predictive model development and model deployment in PI – including the lab manual, see:

https://pisquare.osisoft.com/docs/DOC-3463-predicting-remaining-useful-life-and-equipment-failure-using-a-machine-learning-multivariate-model

During the lab, we will discuss the answers to the questions in this Exercise.

Exercise 4 – Condition assessment rules and asset health score

Objective
Apply the appropriate condition assessment rules to process/equipment measurements and calculate an overall asset health score.

This Exercise is a walk-through; it does not include specific hands-on items

Solution
The solution uses Asset Framework Analytics capabilities to convert a “Raw Value” (PI tag value) to a normalized i.e. a “Case Value” (AF Attribute). And then, by applying a Weight%, it is transformed to a Score.

Thus, each measurement gets a normalized weighted score (0 to 10) by applying a condition assessment rule. And, then the normalized scores are rolled up to arrive at a composite asset health score. The Weight% applied to each attribute depends on its contribution to the asset health.

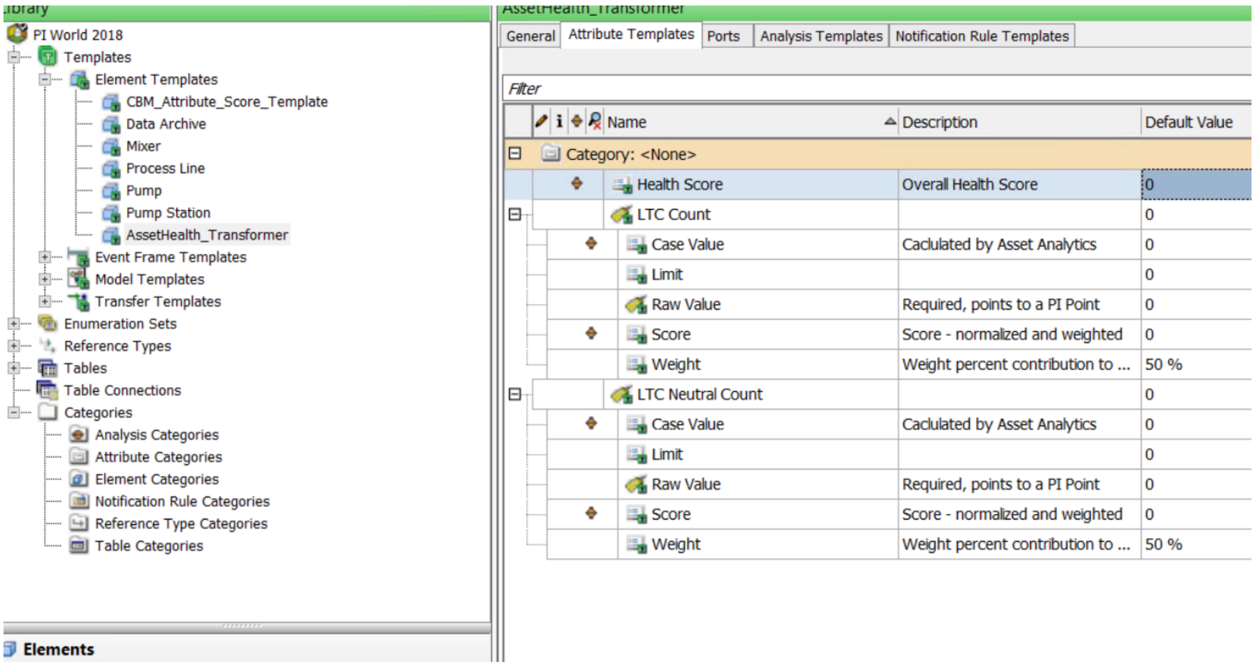
The composite asset health score ranges from 0 to 10 (0=Good, 10=Bad)

Let’s use a Transformer - and consider the following:

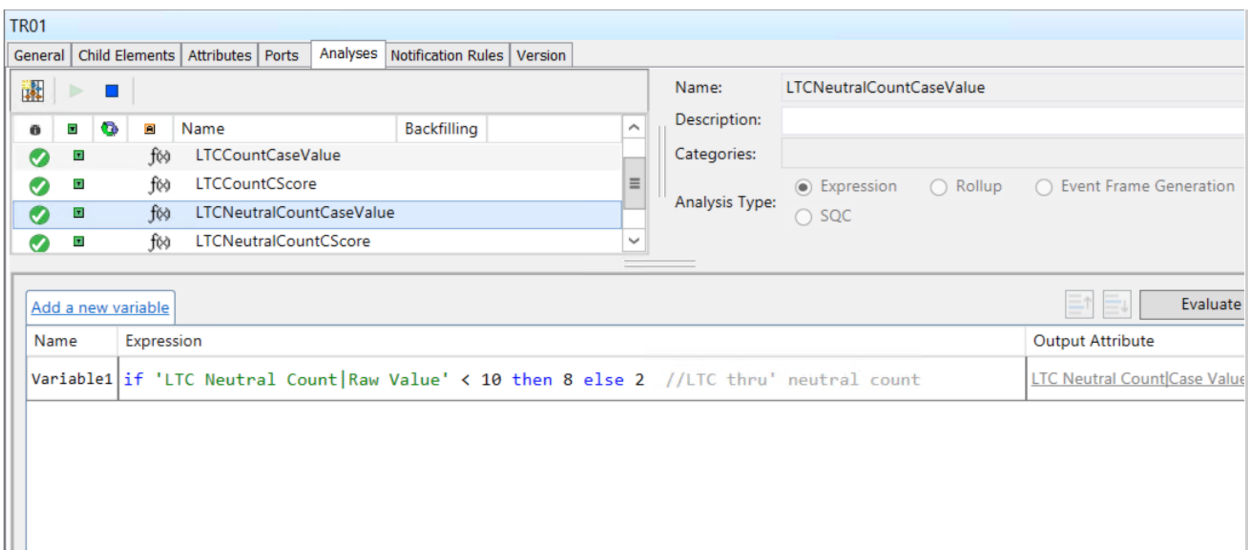
- LTC counter operations (LTC= Load Tap Changer)
- LTC through neutral count
- DGA (dissolved gas analysis) detectable acetylene
- DGA High gas rate of change
- Low dielectric
- High water
- Low nitrogen pressure

For illustration, let’s use the first two, i.e. LTC counter operations and LTC through neutral.

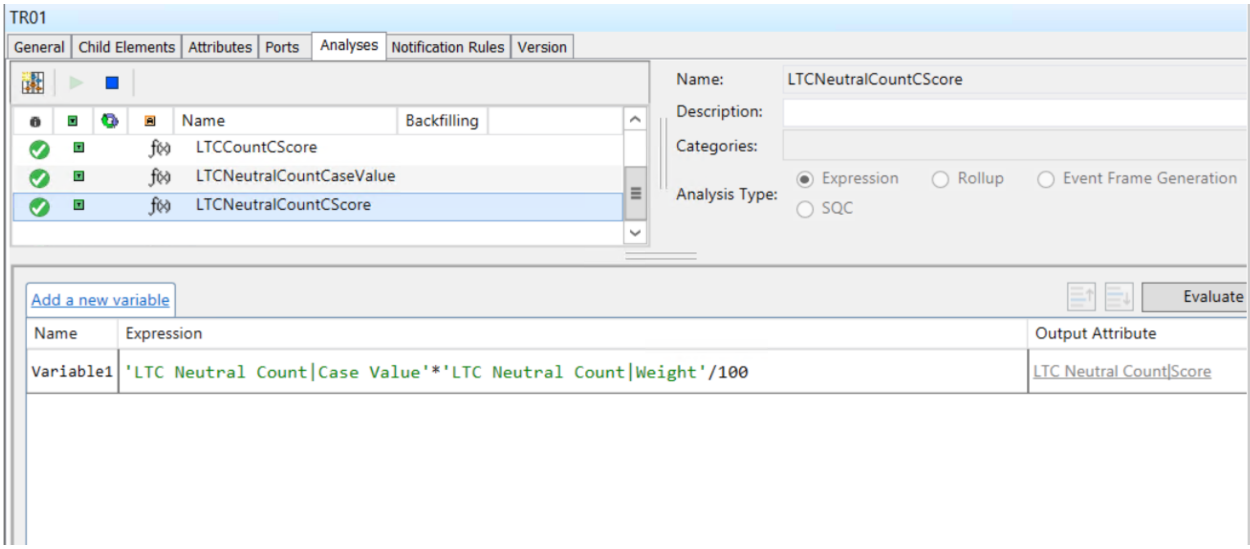
The screen below shows a Transformer template.



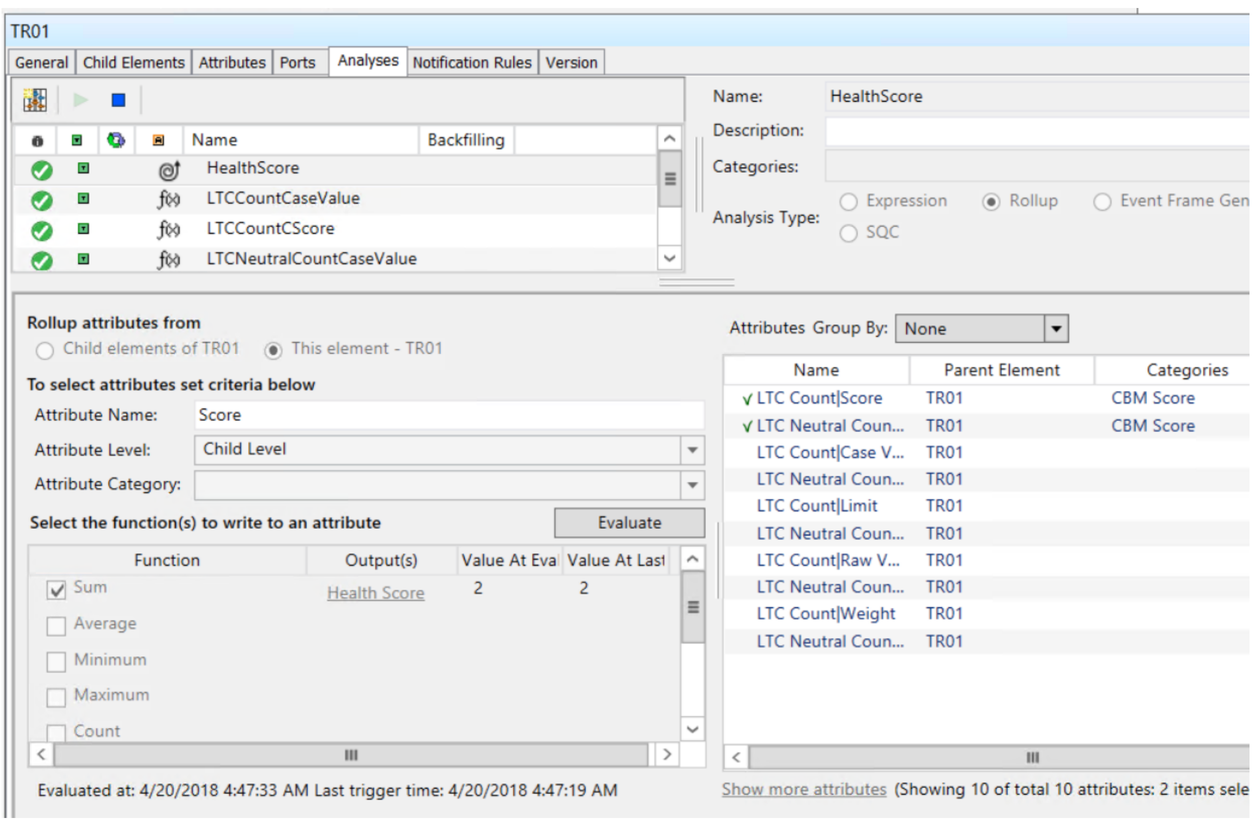
Individual attribute Case value calculation:
Note that the analysis uses “Raw Value” as input and writes to “Case Value”.



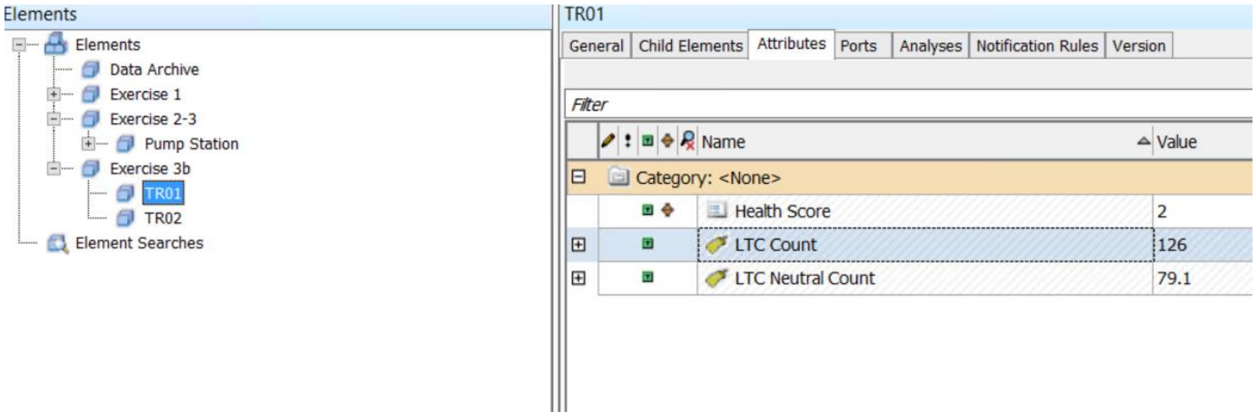
Individual attribute weighted score:



Overall Health Score is a roll up of the individual Attribute scores:



And, as you configure Transformers using these templates, the composite health score is periodically calculated by PI System Asset Analytics.



The composite health score for TR01 is 2 i.e. asset is in good health (0=Good, 10=Bad).


Have an idea how to improve our products?
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https://feedback.osisoft.com/


OSIsoft. Learning
PI SYSTEM LEARNING MADE EASY!
Accelerate success with the new OSIsoft Learning platform.
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