MTBF Pulley

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Summary

This document analyses the pulley failure, by failure we mean **MTBF**, using distribution instead of the geometric mean. The issue we face is the low amount of failures for some **floc**, we then check the technical specification of the device.

It appears than we can not build MTBF for those installed devices as we have to much variations in time to failure, the context must be add to the device type, such factor as the contamination factor should be consider as well as the max load apply, we do not have those values in the data set (see ISO 281 for details).

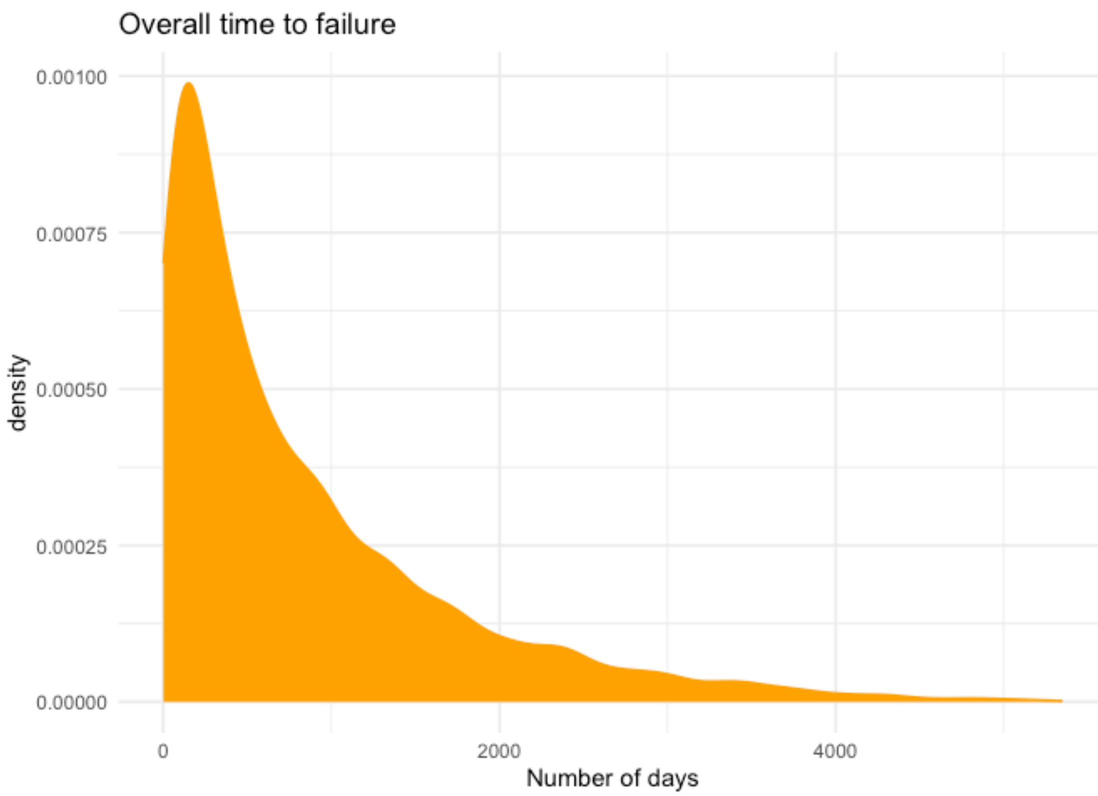
The last part of this document, we use gradient descent to to a prediction on multiclasses on the full dataset, even if we use a hierarchical method the results are pretty interesting.

Data set

The data set has about thirty thousand samples, we check mainly, the FLOC, the failure mode and the scheduled date. We do not have the time between failures, we do a grouping of FLO, and material and sort the schedule date and calculate the differences between dates.

Many samples have been with no failure time, those samples have been excluded from the data set.

The global distribution of time to failure is as follow, we have high gap between failures.



The distribution of failure is from one to seventy seven per functional location, the low number have to be group per material type and failure mode.

Analysing failures

We shall need more attributes per failure, in this case we check the variable description. The distances used:

1. Monge Elkan under construction

The functional location

with one failure

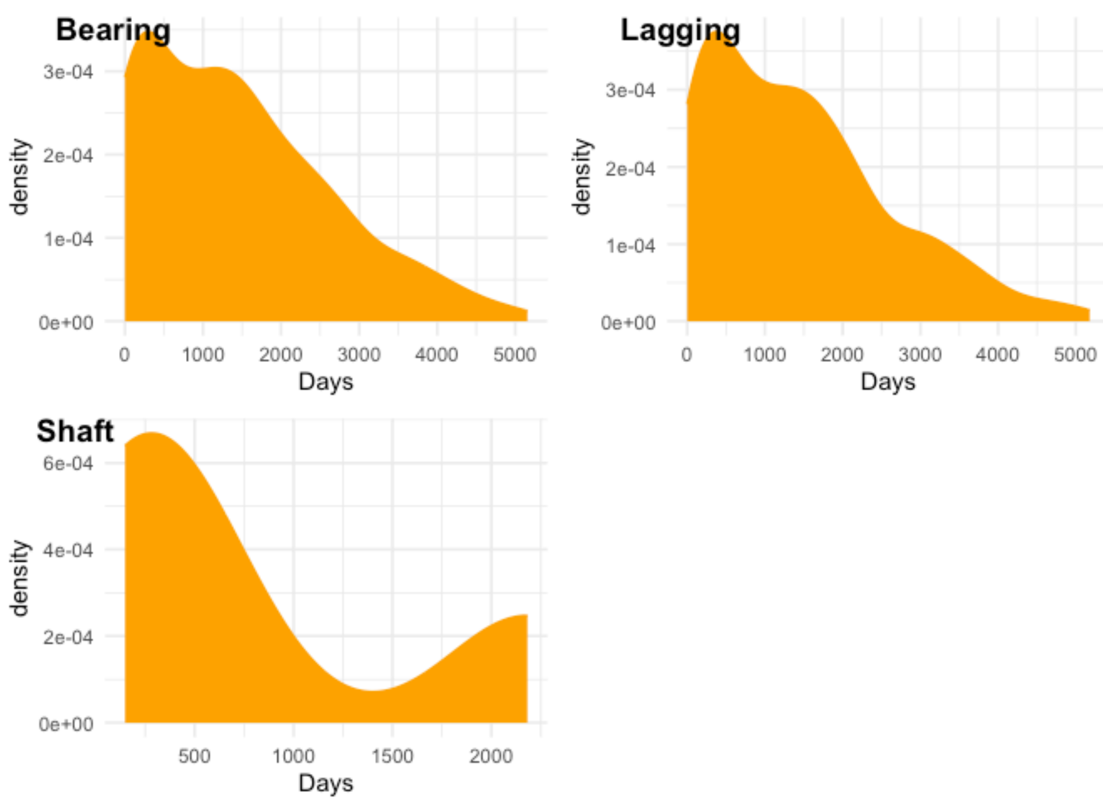
We have `762` functional locations with one error , which are distributed over `318` failure modes during the period considered.

The failure mode for those functional areas are as follow, we can see that we have two main type of failures bearing and belt lagging. The rule of sum is to have thirteen failures to build statistics, we shall select bearing, lagging and shaft.

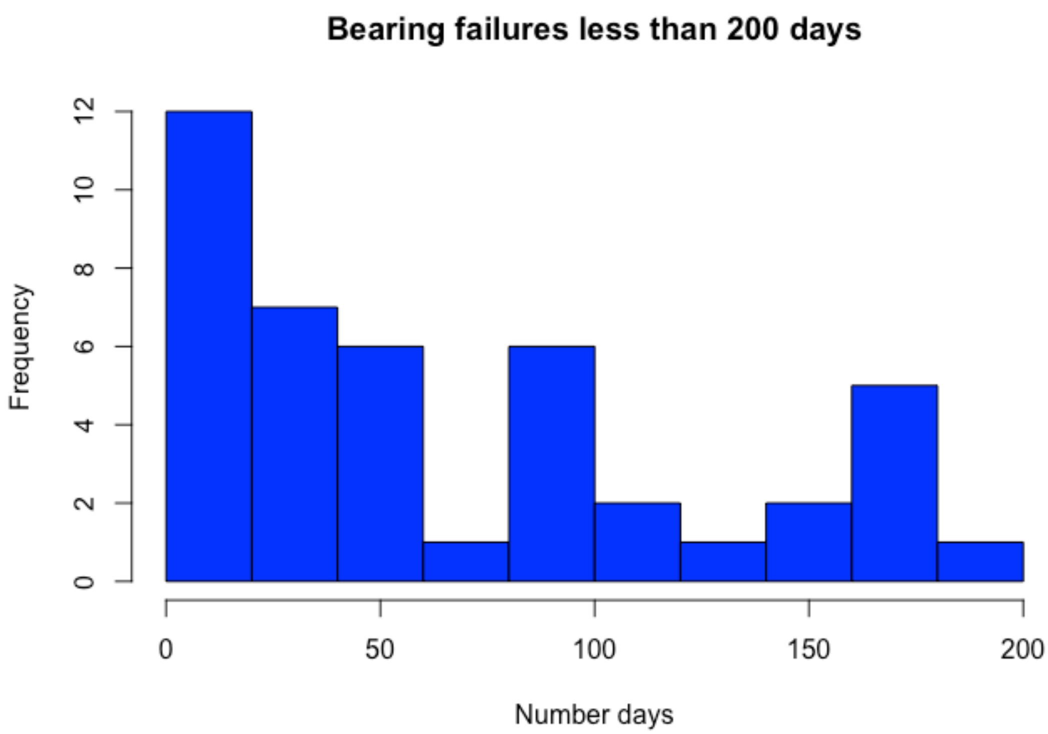
Var1	Freq
Bearing Failure	230
Belt Failure	5
Coupling Failure	1
Idler Failure	4
Insufficient Information	43
Lagging Failure	277

Locking Element Failure	8
Other	12
Planned C/O	21
Shaft Failure	4
Upgraded	14

The distribution for the three failure modes are as follow.

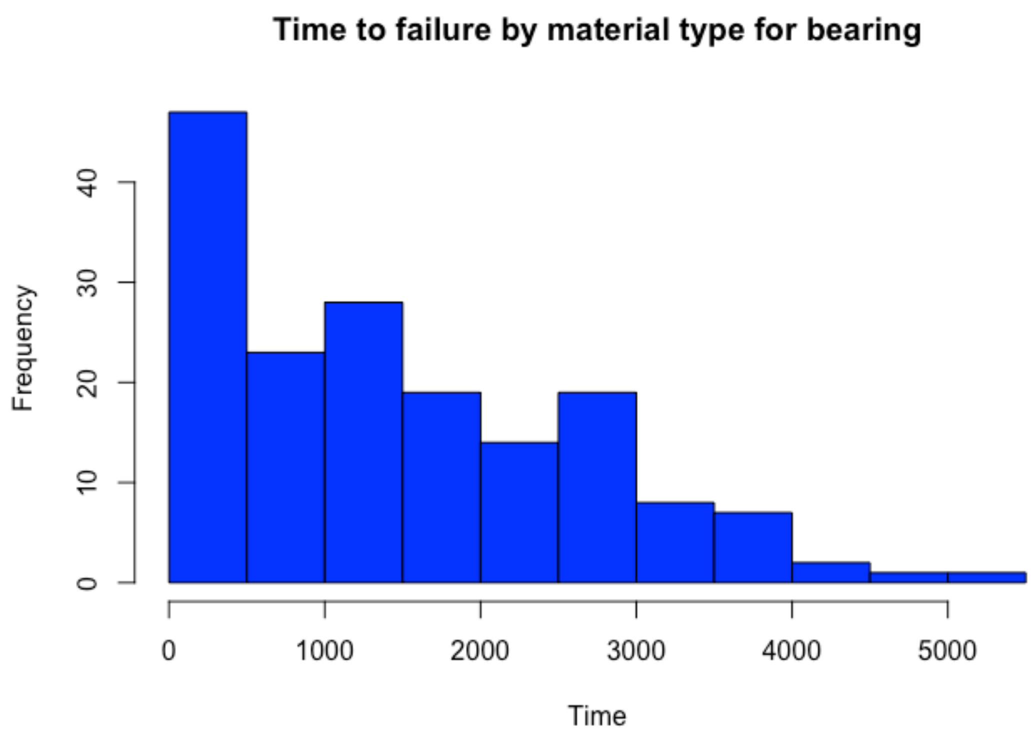


We have a big spread for the three types of failure, The main challenge will be how do we want to use the analysis. Taking the bearing as example the model is in the bin between zero and two hundred days. What is surprising is failure less than 500 days for bearing, in this case we have about 25 failures or 10% of the total bearing failures. This short time could be justify if we have bearing with a certain number of days, as mentioned by **SKF** bearing have a long life time and do not failed so often.



Check with material description

We work with material description for **floc** with one failure, The material description defines the technical specification of the device, it is a category. We show the distribution of the mean time based on the material type, we ca notice the spread on the time as well as a deceasing exponential, with most failing before 500 days.



The low time between failure, which is between zero and and less than 50 mean and median are as follow. We have 13 devices with a time to failure less than 50 days,

x
HOUSING;BRG UNIT;CLOSED;FSSN532TACVMA/SG
PULLEY ASSEMBLY;CONV;DR;SANDVIK;06151
PULLEY ASSEMBLY;SANDVIK;BP00034862
PULLEY,CONV;1600MM OD;1650MM FACE
PULLEY,CONV;SANDVIK;BP00072531
PULLEY,SHAFT;SANDVIK;BP00066000
PULLEY,SMALL DIA;SANDVIK;BP00060248
PULLEY;CONV;610MM OD;SHELL;HI P0019628
PULLEY;CONV;915MM OD;SHELL;HI P0019668
PULLEY;CONV;DR;1370MM W;PROK 995558/2
PULLEY;CONV;DR;HI 12001H
PULLEY;CONV;HD;832MM OD;2050MM FACE

PULLEY;SANDVIK;05301-3

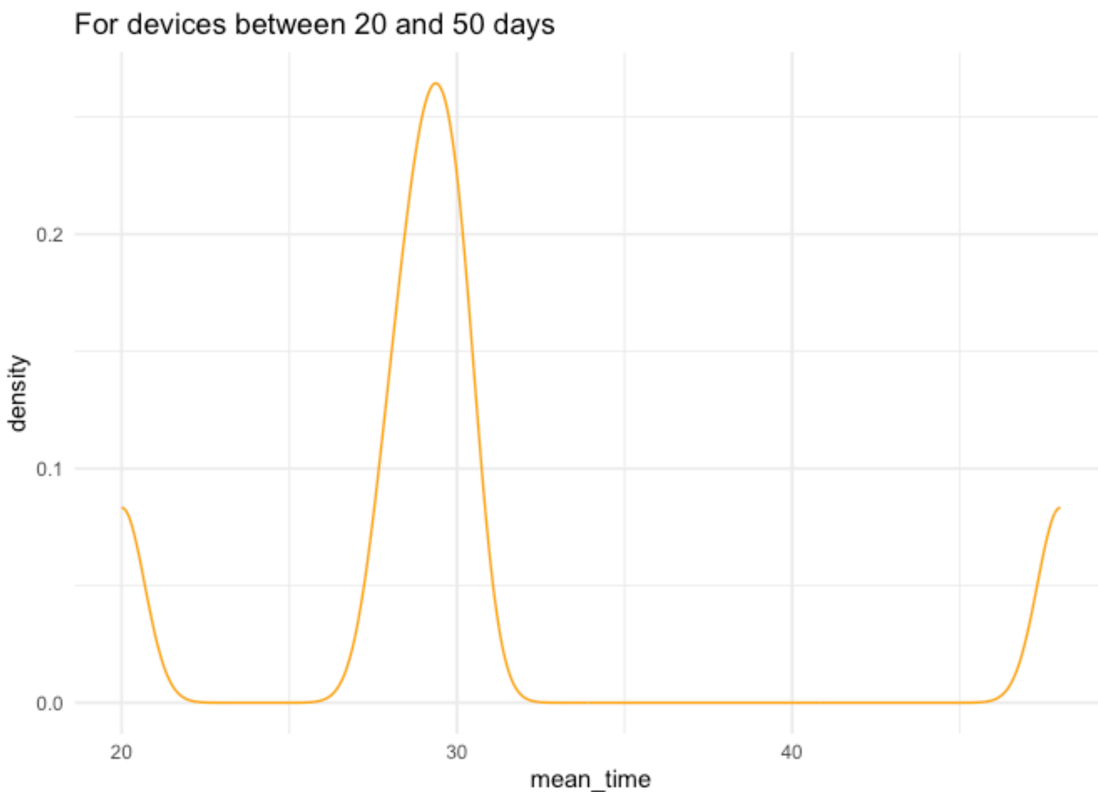
With this data set we have a MTBF of about `18.12`, but standard deviation of `15.3`, which show that for the duration less than 50 days we can not deliver reliable MTBF. The sample consider is of thirteen samples acceptable size for statistics.

We analyse the devices with a failures greater or equal to twenty and less than fifty days, as we have gap between eight and twenty days in previous sample, we should not consider the bearing for those small values.

material_description	mean_time
HOUSING;BRG UNIT;CLOSED;FSSN532TACVMA/SG	30
PULLEY ASSEMBLY;CONV;DR;SANDVIK;06151	29

PULLEY,CONV;1600MM OD;1650MM FACE	29
PULLEY,SHAFT;SANDVIK;BP00066000	20
PULLEY,SMALL DIA;SANDVIK;BP00060248	28
PULLEY;CONV;DR;1370MM W;PROK 995558/2	48
PULLEY;SANDVIK;05301-3	30

The distribution for those devices is as follow, the distribution is quite unusual, but we use kernel here, the other point we deal with intermittent data, therefore a type such as **Cruston** will define the distribution and able to generate of forecast, the forecast will predict on the whole but not for a particular device. We still have a standard deviation of eight, which mean the lower extreme is as 12 days, which make inspection quite often. If the failure was recurring if will be perhaps better to change bearings.



High failure time for one sample

The same but for device with mean time greater than 4000 days, those material number are unique over all the the bearing data set.

material_description	mean_time
PULLEY,CONV;DR;1676MM W;P-001-30497	4138

PULLEY,DRIVE,COMP,C011,W999-M-302	4335
PULLEY;CONV;1220X914MM;HI 42D	4820
PULLEY;CONV;PROK 997780	5155

The pulley category as follow, we do not have snub or bend in this sample.

Var1	Freq
General	2
Head	1
Tail	1

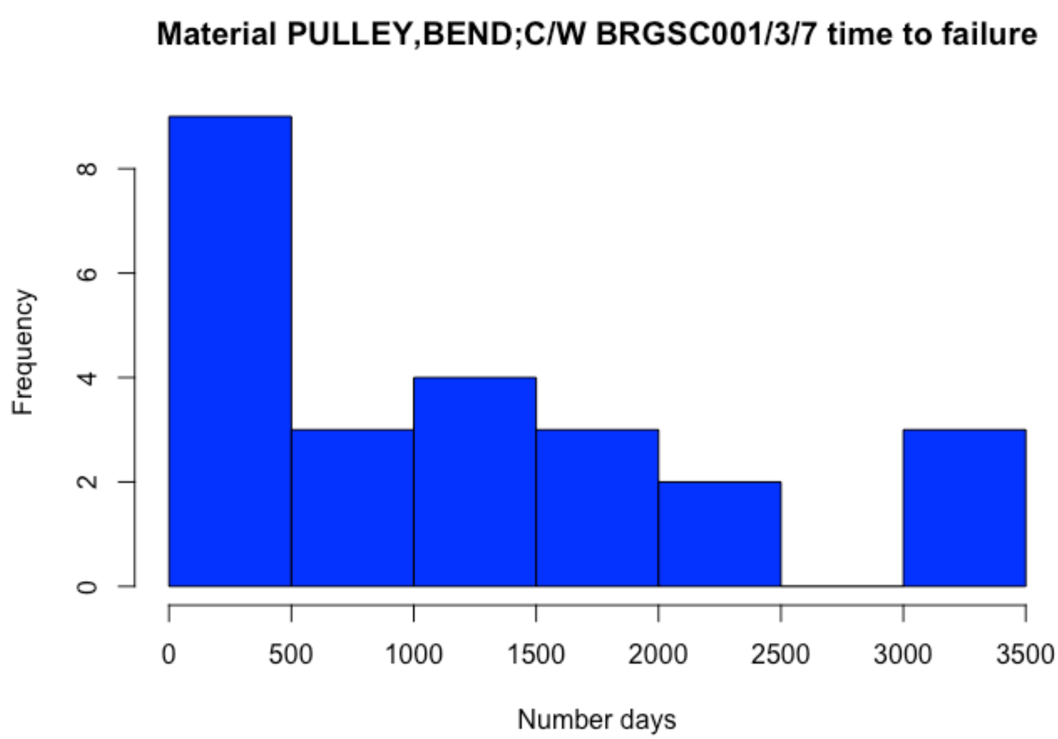
Analysis more than one device

In this sample rebuilt with slection of materail description, we have same devices with significant difference in time to failure. It means we have conditions, which will reduce the time to failure in this case. It appears that we have few exceptions with low time to failures, which must be analysed.

What is a surprise is the spread of time to failures, concerning the same material description, as shown below we could have more than 2000 days difference in time to failure for the same material description.

Analysis same materail description

As example, for the device **PULLEY,BEND;C/W BRGSC001/3/7** which has a mean of 693 days and median of 2 days, for the whole data set, that is `24` samples, the histogram shows the distribution.

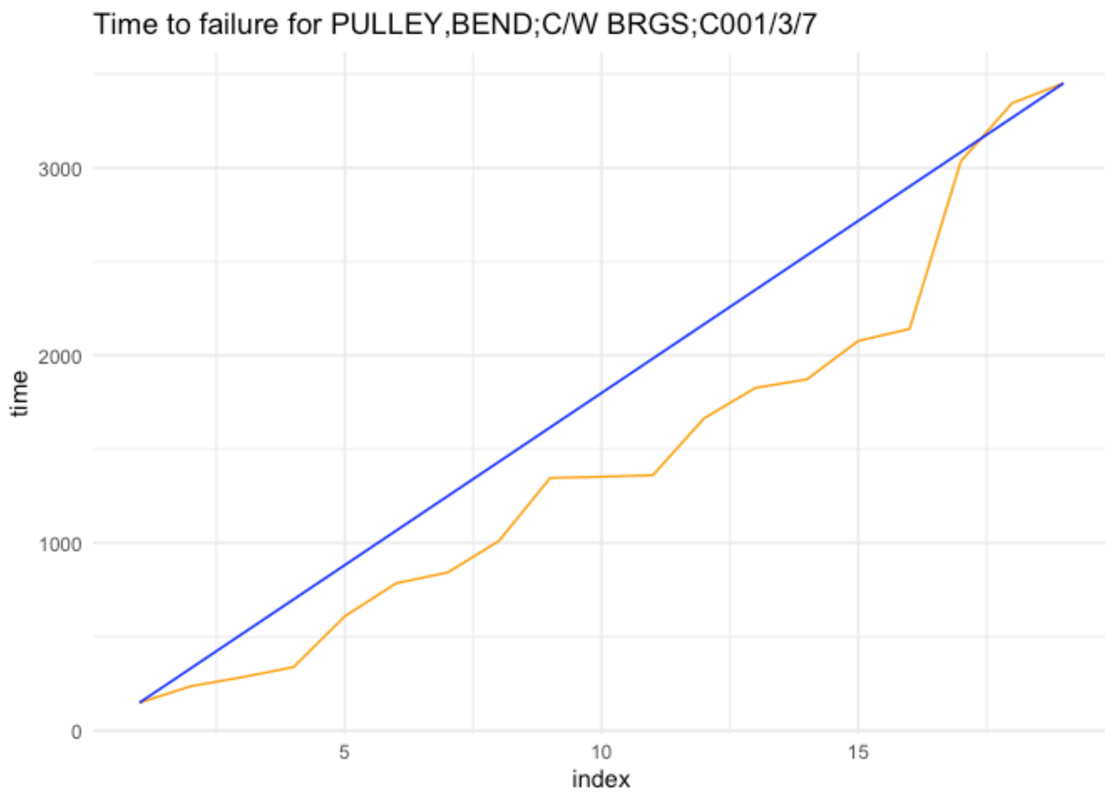


Build four failure categories <100, 100 to 500, 500 to 2000 and more than 2000 days to failure we have have the following. The bulk is between 500 days a and 2000 days which is a a wide range.

Var1	Freq
[0,100]	5
(100,500]	4
(500,2e+03]	10
(2e+03,3.5e+03]	5

Evaluating one contamination factor

This chapter should be taken with a pitch of salt, as we try to figure out a contamination factor, ignoring the variation in load. The basic rating life is taken as the maximum in this case 3451 days, we exclude from the data set the bearing with less than 85 days of time between failure.



We calculate the coefficient of contamination as mentioned, which are, those value have to be adjust with time:

time	ref	coef
148	148.0	0.0428861
236	331.5	0.0683860
284	515.0	0.0822950

338	698.5	0.0979426
609	882.0	0.1764706
785	1065.5	0.2274703
842	1249.0	0.2439873
1010	1432.5	0.2926688
1346	1616.0	0.3900319
1353	1799.5	0.3920603
1361	1983.0	0.3943784
1665	2166.5	0.4824688
1827	2350.0	0.5294118
1872	2533.5	0.5424515
2077	2717.0	0.6018545
2141	2900.5	0.6203999
3035	3084.0	0.8794552

3345	3267.5	0.9692843
3451	3451.0	1.0000000

This device is across multiple functional location and but same plant, the functional loacation are as follow, we can notice the difference in time to failure inside a functional location, which add a complication.

functional_location	failure_time	pulley_category	description
3018C001 ELEMPULL .BEP1	609	Bend	C/O C001 Pulley #2
3018C001 ELEMPULL .BEP1	1872	Parent	C001 Bend Pulley 2 Lagging
3018C001 ELEMPULL .BEP1	1346	Bend	C001 Pulley 2 C/O

3018C001 ELEMPUL L .BEP2	1665	Bend	C001 Bend Pulley 4 C/O
3018C001 ELEMPUL L .GTUP	3035	General	C001 GTU Pulley 3 Lagging
3018C001 ELEMPUL L .GTUP	1353	General	C001 GTU Pulley 3 C/O
3018C001 ELEMPUL L .TAPU	1361	Tail	C001 C/O Pulley # 5
3018C001 ELEMPUL L .TAPU	785	Tail	C001 C/O Pulley 5 (Tail)
3018C001 ELEMPUL L .TAPU	1010	Tail	C001 Tail Pulley 5 C/O

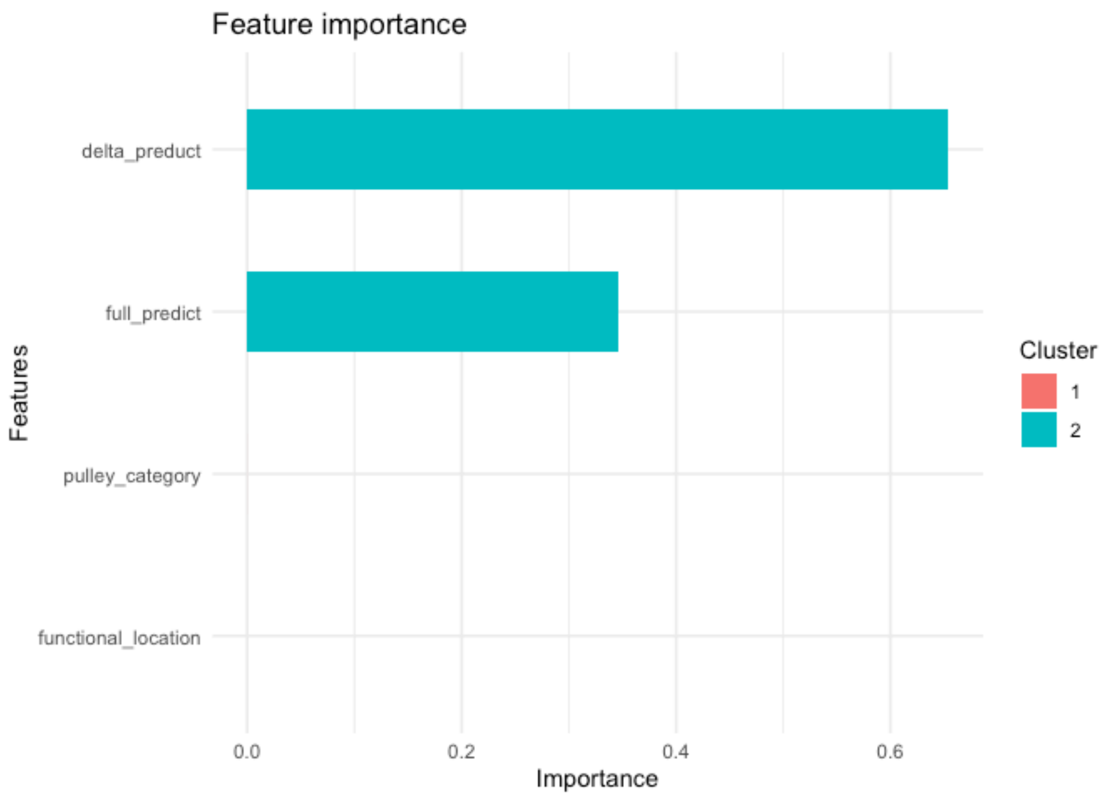
3018C001 ELEMPUL L .TAPU	842	Tail	C001 C/O Tail Pulley
3018C001 ELEMPUL L .TAPU	3	Tail	C001 C/O Tail Pulley
3018C001 ELEMPUL L .TAPU	148	Tail	C001 C/O Tail Pulley
3018C003 ELEMBEL T	236	??	C003 C/O Pulley 2 - Lagging worn
3018C003 ELEMPUL L .BEP1	2077	Bend	C003- C/Out Pulley # 2- Bend Pulley
3018C003 ELEMPUL L .BEP2	1	Bend	C003 C/O N0 4 PULLEY BEND

3018C003 ELEMPUL L .TAPU	3451	Tail	C003 C/O Tail Pulley #5
3018C003 ELEMPUL L .TAPU	284	Tail	C003 C/O Tail Pulley No.5
3018C003 ELEMPUL L .TAPU	3	Tail	C003 C/O Tail Pulley No.5
3018C007 ELEMPUL L .BEP1	2	Bend	C007 #2 Pulley C/O
3018C007 ELEMPUL L .BEP3	3345	Bend	C007 Pulley 5 re-lag
3018C007 ELEMPUL L .BEP3	338	Bend	C007 Bend Pulley 5 C/O P3

3018C007 ELEMPULL .TAPU	2141	Tail	+ C007 Pulley 07 Change Out
3018C007 ELEMPULL .TAPU	1827	Tail	C007 C/O Tail Pulley #7 Lagging Worn
3018C007 ELEMPULL .TAPU	85	Tail	C007 C/O Tail Pulley #7 Lagging Worn

Considering the full data set

We make the hypothesis that the environment influence the time between failure, therefore we have a factor to difine to do so we consider the full data set with bins. One challenge is the number of functional location of more than 1500.



We have a prediction on numaric and therefore we recalibrate, the confusion is a sbelow, we certainly overfir in this case, but we show that we can have a pretty good prediction on class of time to failure.

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    1    2    3    4
##          1  837    0    0    0
##          2    0 1987    0    0
##          3    0    0 2441    0
##          4    0    0    0  493
##
```

```
## Overall Statistics
##
##                Accuracy : 1
##                  95% CI : (0.9994, 1)
##     No Information Rate : 0.4239
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 1
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 1 Class: 2
Class: 3 Class: 4
## Sensitivity            1.0000   1.0000
1.0000  1.00000
## Specificity            1.0000   1.0000
1.0000  1.00000
## Pos Pred Value         1.0000   1.0000
1.0000  1.00000
## Neg Pred Value         1.0000   1.0000
1.0000  1.00000
## Precision              1.0000   1.0000
1.0000  1.00000
## Recall                 1.0000   1.0000
1.0000  1.00000
```

```
## F1                          1.0000   1.0000
1.0000  1.00000
## Prevalence                  0.1454   0.3451
0.4239  0.08562
## Detection Rate              0.1454   0.3451
0.4239  0.08562
## Detection Prevalence        0.1454   0.3451
0.4239  0.08562
## Balanced Accuracy           1.0000   1.0000
1.0000  1.00000
```

Building an universal model

The previous chapter does not use a test set, in this section we shall use a training set made of .9 of the initial data set and a test set. We do not manage without rebuilding models as shown below, we use a tree method and therefor the model could change drastically with few data changes as it is the case here

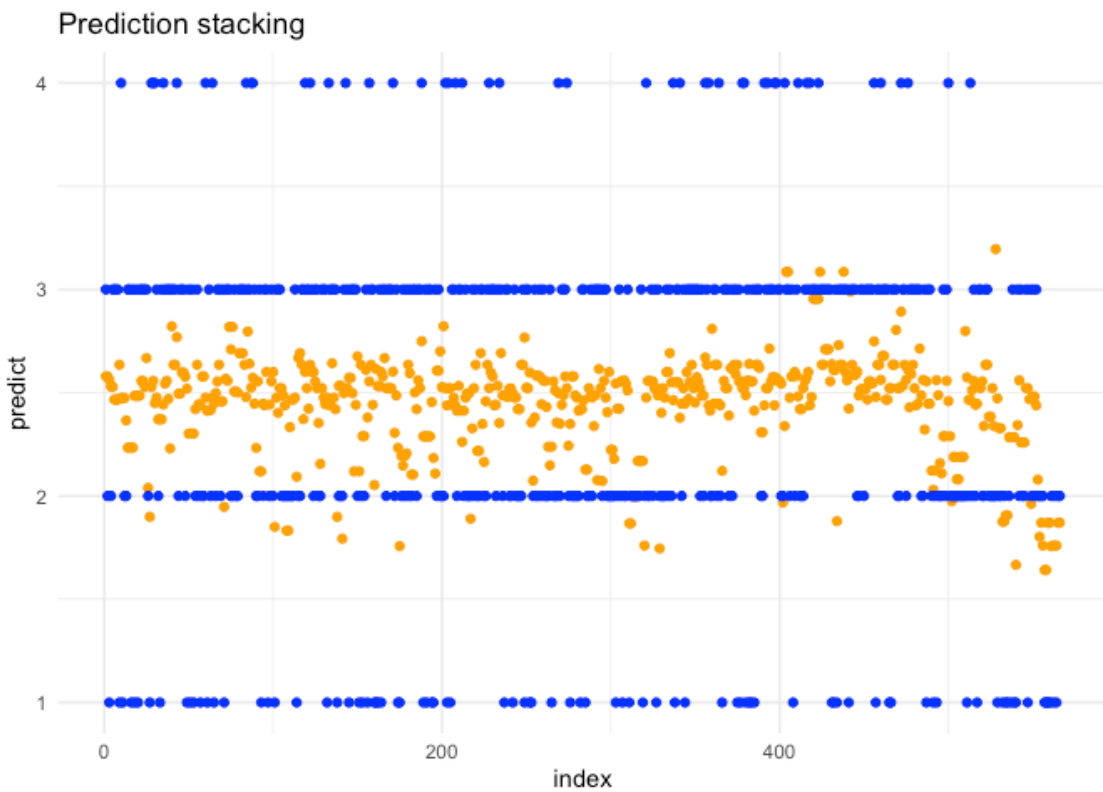
```
## Confusion Matrix and Statistics
##
##             Reference
## Prediction   1   2   3   4
##          1   6   3   1   0
##          2  51 111  85  19
##          3  26  84 156  29
##          4   0   0   2   1
```

```
##
## Overall Statistics
##
##                Accuracy : 0.4774
##                  95% CI : (0.4358, 0.5191)
##     No Information Rate : 0.4251
##     P-Value [Acc > NIR] : 0.006537
##
##                   Kappa : 0.1553
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##                      Class: 1 Class: 2
Class: 3 Class: 4
## Sensitivity           0.07229   0.5606
0.6393 0.020408
## Specificity           0.99185   0.5878
0.5788 0.996190
## Pos Pred Value        0.60000   0.4173
0.5288 0.333333
## Neg Pred Value        0.86348   0.7175
0.6846 0.915937
## Precision             0.60000   0.4173
0.5288 0.333333
## Recall                0.07229   0.5606
```

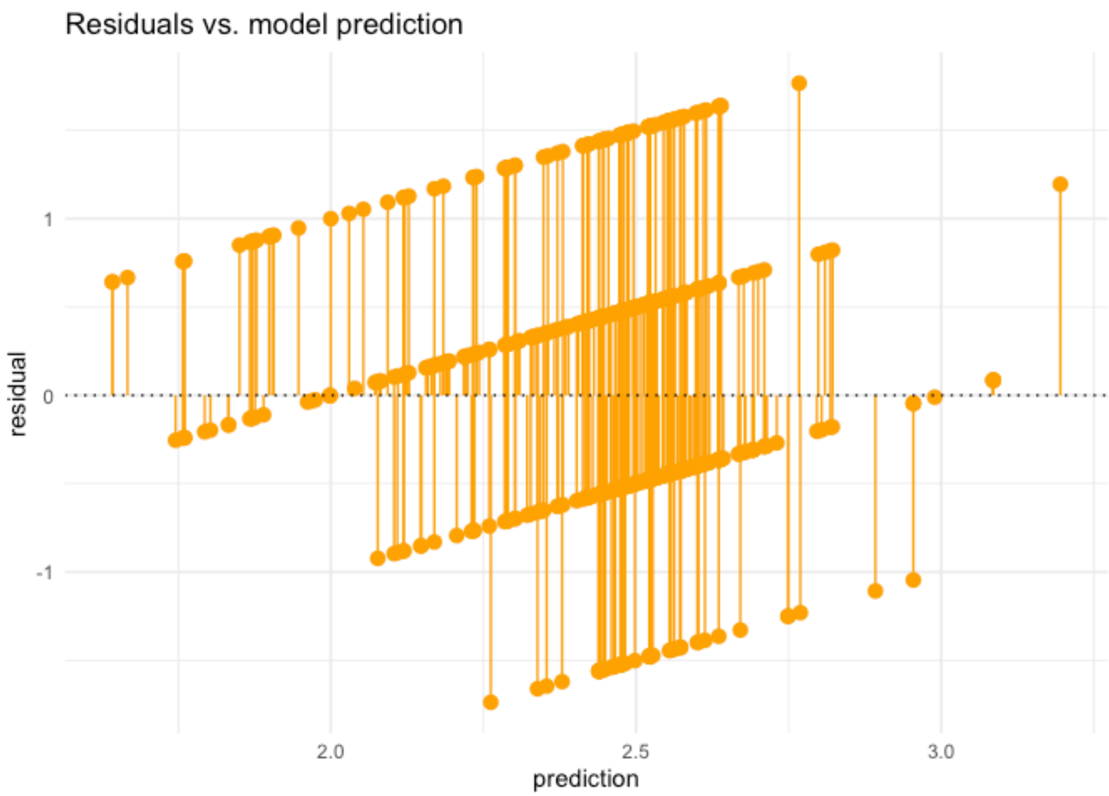
```
0.6393 0.020408
## F1                    0.12903   0.4784
0.5788 0.038462
## Prevalence            0.14460   0.3449
0.4251 0.085366
## Detection Rate        0.01045   0.1934
0.2718 0.001742
## Detection Prevalence  0.01742   0.4634
0.5139 0.005226
## Balanced Accuracy     0.53207   0.5742
0.6091 0.508299
```

Ensemble

In this section, we build an ensemble model, we use **caretEnsemble** to build the ensemble. We can notice that the prediction with two models **glm**, **random forest** and **boostimg tree* is not accurate. We shall never go toward one or four.



The residual versus the predicted is show below, we have an increase ir decreas in resiudal futher in valuw we predict.



Residuals vs. model prediction
1
0
-1
residual
2.0
2.5
3.0
prediction