Reducing inspection by using soft sensors

ASQ - 2019 Inspection Division Conference

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Presentation goal

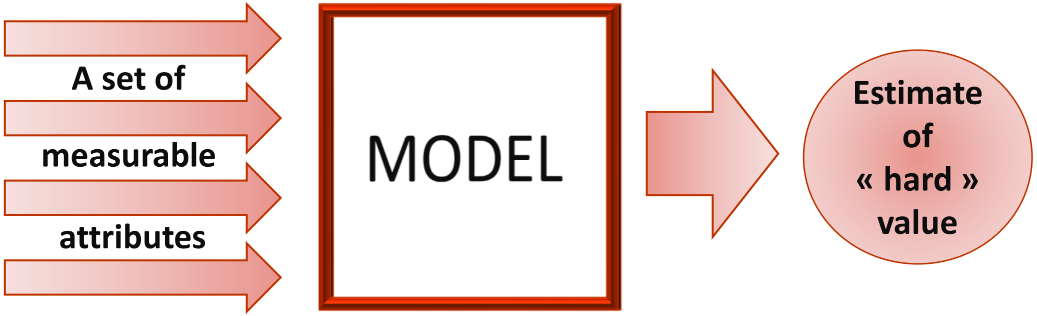
- In many organizations, a lot of process data is captured automatically from sensors & transmitters
- Those process data can often be used to predict quality characteristics of the final product
- In this presentation you will learn how we can use process measurements to predict the result of a final inspection test resulting in lower inspection cost and faster learning on the process

Presentation content

- What is a soft sensor
- Advantages of soft sensors
- Steps in building a soft sensor
- Application example: The tensile strength lab test
- Conclusion

What is a soft sensor

≡ *The term “soft” is for software, because the sensor values are typically coming from a model (equation) which is calculated using a software, and “sensor”, because the model is delivering information similar to an hardware sensor*

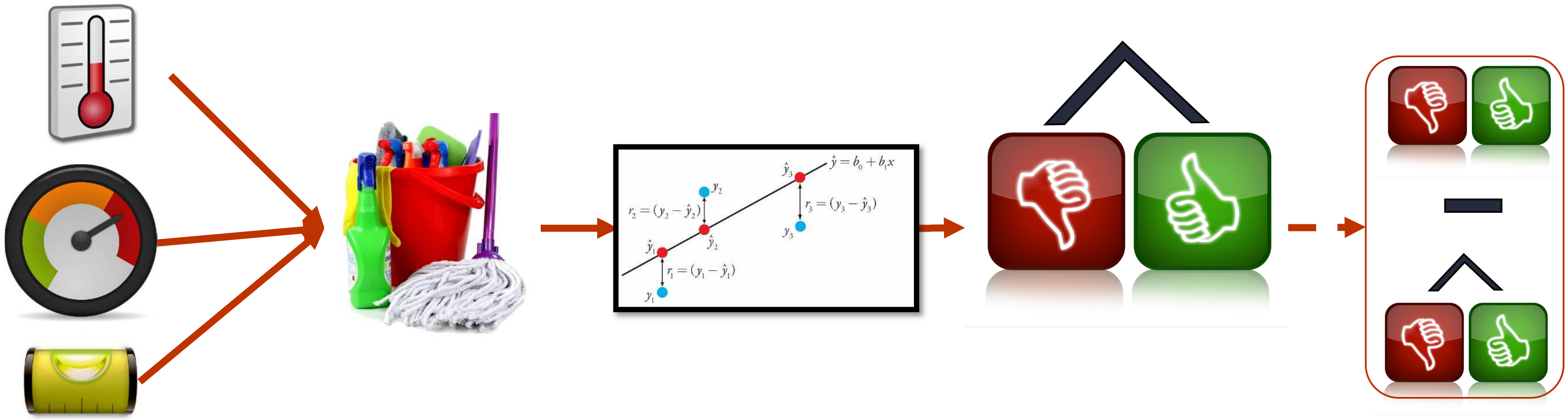


Advantages of soft sensors

- Perform real-time monitoring and control (if soft sensor is built with factors measured at a high frequency)
- Can estimate parameters in situations where no hardware sensor is available
- Low-cost alternative to expensive in-line hardware devices
- Reduce cost associated to lab resources by reducing the frequency of lab tests
- Can be used to create a redundant measurement that allows to automate the check for a drift in a hard or soft sensor calibration
- Helps in understanding the factors affecting a response and improves learning speed of a process

Five steps to build a soft sensor

1. Identify predictors
2. Clean and screen data
3. Select, train and validate model
4. Monitor & adjust process based on predicted values
5. Monitor model adequacy using residuals



Five steps to build a soft sensor

1. Identify predictors

- Identify factors that have a relationship with the quality characteristic inspected
- Those factors should typically be measured more frequently than the quality characteristic

2. Clean and screen data

- Assess if the data from the sensors are reliable
- Make sure the transmitters are calibrated and accurate
- Assess if there are any outliers and why – consider improving the robustness of the transmitter
- Evaluate if it is possible to screen the data using basic rules

3. Select, train and validate model

- Build a prediction model where the factors measured by sensors are used to predict the quality characteristic
- Consider using a training set and a validation set
- Evaluate if the model is adequate for replacing some inspections of the quality characteristic

4. Monitor & adjust process based on predicted values

- Use the predicted values to monitor the quality characteristic
- If the quality characteristic is compared to specs, consider using tightened specs to manage the risk of accepting a bad product

5. Monitor model adequacy using residuals

- At a set frequency, compare the model prediction to a « real » measurement of the quality characteristic
- If the residuals show a trend or excessive variability, search for the cause and consider going back to more inspection (the identification of a trend in residuals can often be automated)

Even before considering a soft sensor …

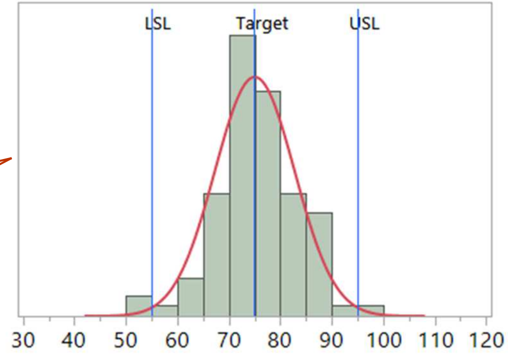
- In a situation where one considers replacing quality inspections using a lab test by monitoring using a soft sensor, one should typically consider the actual process capability to meet the specification

A soft sensor will always have some degree of prediction error which will lead to questionning the soft sensor value especially when it is close to specification limits

Is the process capability adequate?

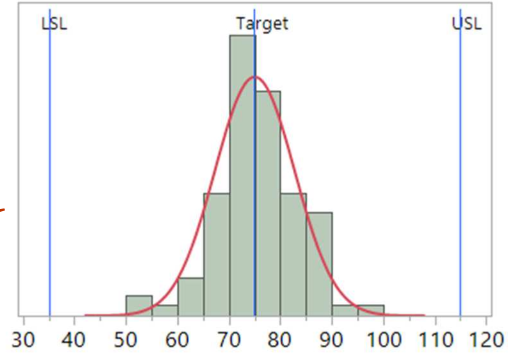
- **Situation 1**: The actual process produced 2% defects for the last 1000 products

There could be many situations where it will be hard to judge if the product is good or bad because the prediction will be close to the specification limit



- **Situation 2**: The actual process did not produce any defects for the last 1000 products

The products are far enough from the specification limits to probably allow to make good decisions on product quality even in the presence of prediction error



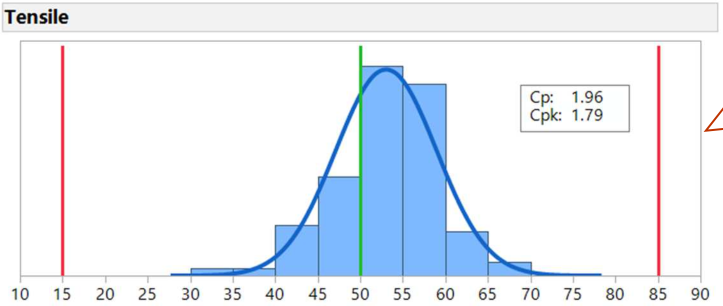
Soft sensor – Example

Context:

- The tensile strength is an important quality characteristic of a product
- The specifications are:
  - LSL = 15 and USL = 85
- The test is performed on one product every hour and is taking 50% of a lab technician time in addition to be expensive to perform since it is destructive
- Implementing a soft sensor could save a lot of money $ by saving products from being destroyed and making the lab resource available to perform tests that are outsourced today

Is the process capability adequate?

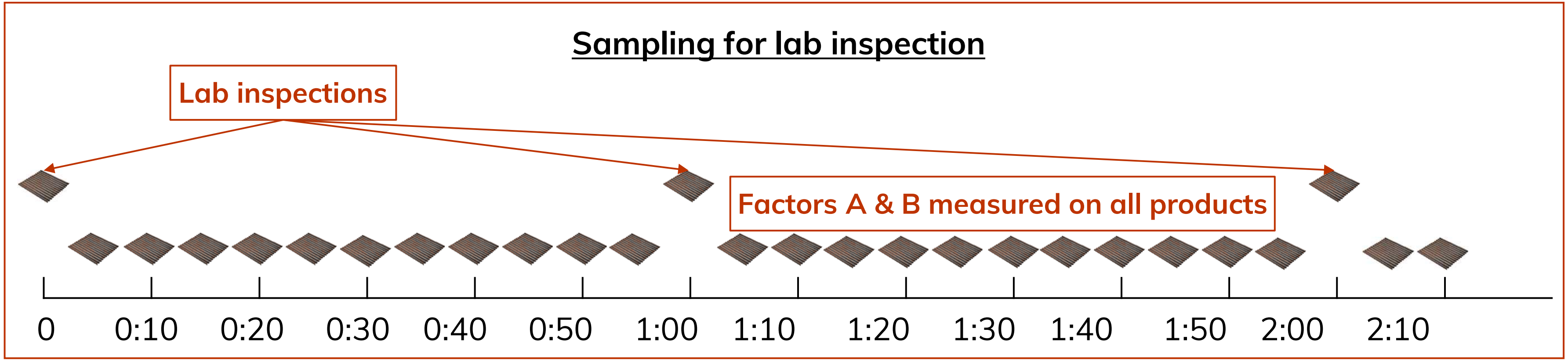
- Before considering using a soft sensor to reduce inspection, let’s look at the process capability
- The process capability is acceptable since the probability of observing an out-of-spec product is low

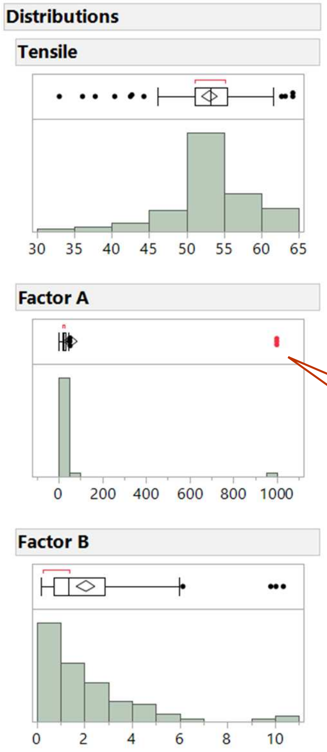


We have some room for additional variation from a soft sensor prediction error

Two factors are good predictors of the tensile strength

- Factor A measured on every product by a transmitter
- Factor B measured on every product by an in-line automated testing equipment





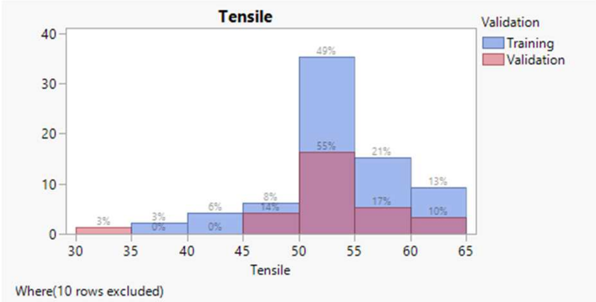
- The calibration of sensor (Factor A) and in-line equipment (Factor B) were checked and they were OK
- Both factors were graphed to identify potential outliers

Those values are not possible (999).

They happen when the sensor connection to the network is failing.

A program was made so they will be automatically replaced by missing values in the prediction data set.

- A training set (70% of data) and a validation set (30%) were built
- The model was built using the training set and the validation set
  - The model explains 96% of the variation in the tensile training set and 94% of the variation in the tensile validation set
  - The model error is 1.33 in the validation set



	Training	Validation
R^2	96%	94%
Error	1.04	1.33
Residuals diagnostic	- Normally distributed - Homogeneous variance - Independent	- Normally distributed - Homogeneous variance - Independent

- The model equation:
  - 50.0 + 0.3*FactorA – 2.1*FactorB
    - Example: 50 + 0.3*10.2 -2,1*2.22 = 48.5

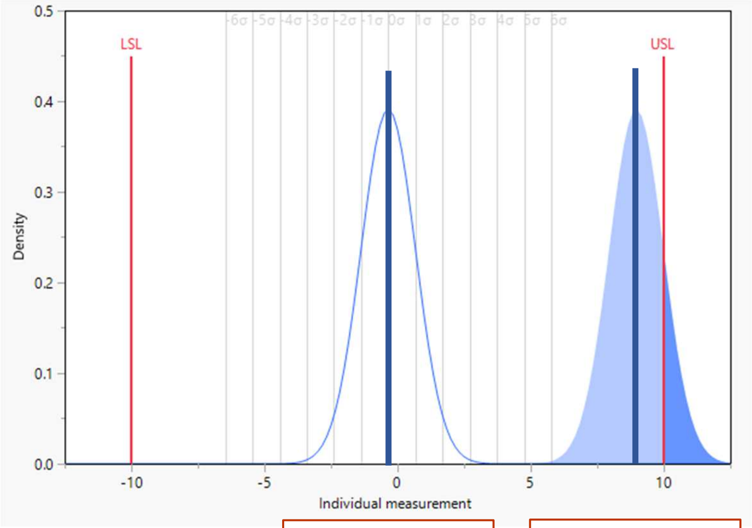
Factor A	Factor B	Tensile	Pred Formula Tensile	Residuals Tensile
10.2	2.22	47.4	48.5	-1.1
7.5	9.82	33	32	1
27	0.84	56	56.4	-0.4
21.9	4.58	46.1	47.2	-1.1

- Residuals are obtained from the following calculation:
  - Tensile – Predicted Tensile
    - Example: 47.4 – 48.5 = -1.1

Is the soft sensor error acceptable?

- **Situation 1**: Even with the variability in the soft sensor prediction (model error), we can conclude the product is within spec
- **Situation 2**: With the variability in the soft sensor prediction (model error), the product could be within spec or outside spec

Variability around a prediction

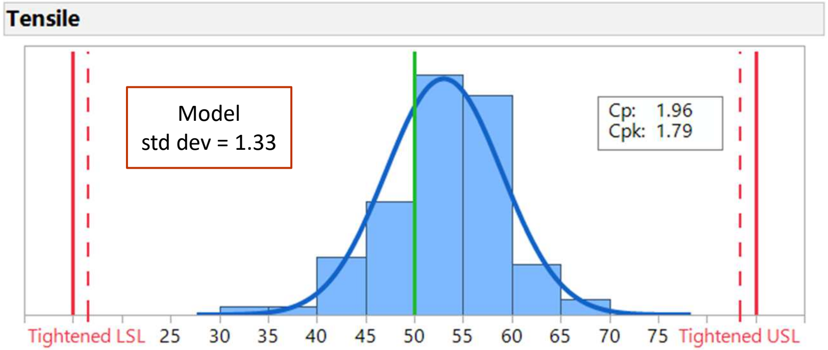


Situation 1

Situation 2

Consider tightening the specs to compensate for the prediction error

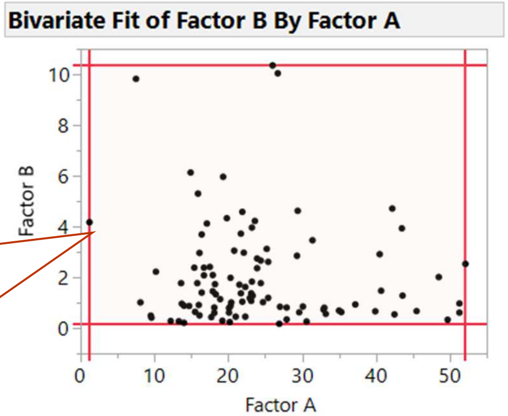
- If we tightened the specifications by 2*0.675*1.33 = 1.8 then, if a prediction is within the tightened specs, there is at least 96% chance its observed value would be within spec.



1. Identify predictors → 2. Clean and screen data → 3. Select, train and validate model → **4. Monitor & adjust process based on predicted values** → 5. Monitor model adequacy using residuals

- Since values from factor A and B are obtained for each product, a prediction can be calculated and the process can be adjusted according to the result

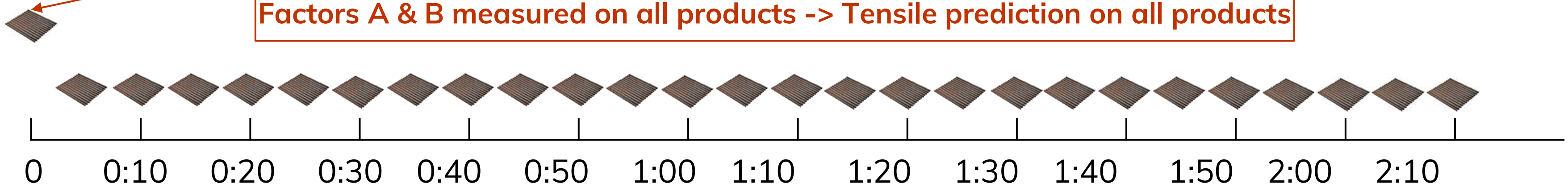
The values for Factor A and B should be within the model range



Sampling for lab inspection

Lab inspection every 8 hours

Factors A & B measured on all products -> Tensile prediction on all products



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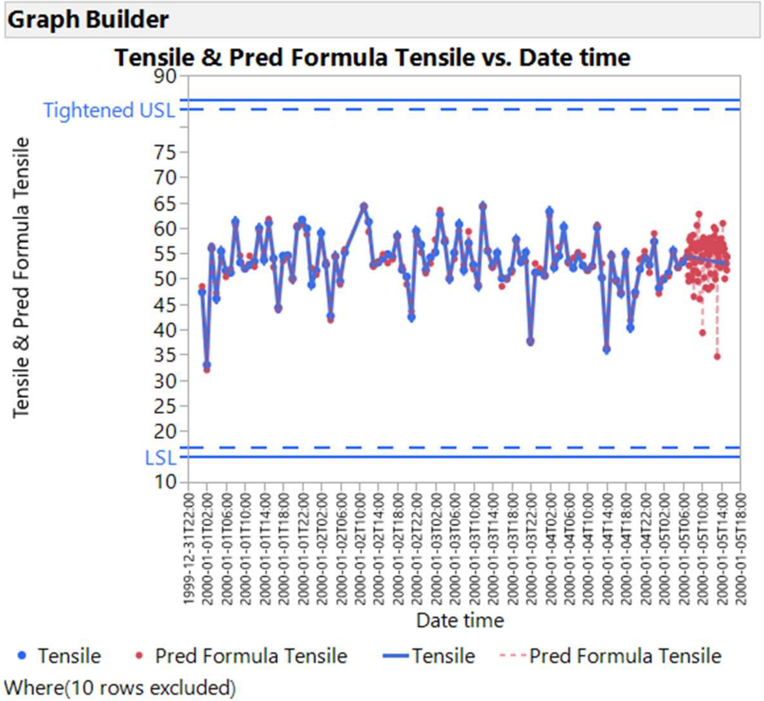
- There is a prediction for each product (in red)
- The prediction can be used to detect out-of-spec products and/or to adjust the process



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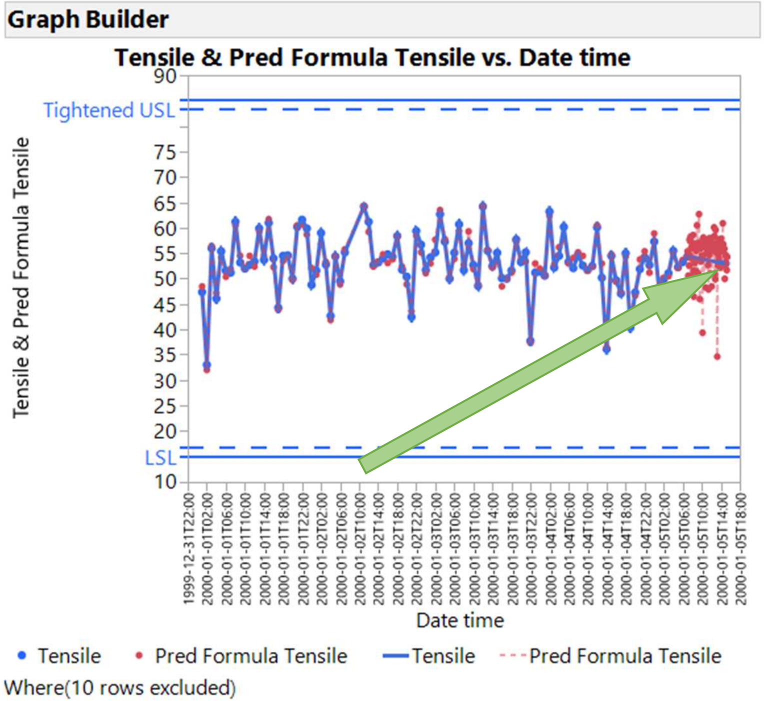
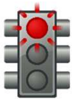
- Every 8 hour, the model precision and accuracy is validated by performing a « real » tensile test and conparing the result to the prediction
- This step is very similar to monitoring the calibration of any measuring instrument



- If the soft sensor performance is « normal », the difference between the lab tensile and the soft sensor prediction should be within ±3σ where σ is the model error
- Here, we would have ±3σ = ± 3*1.33 = ±4

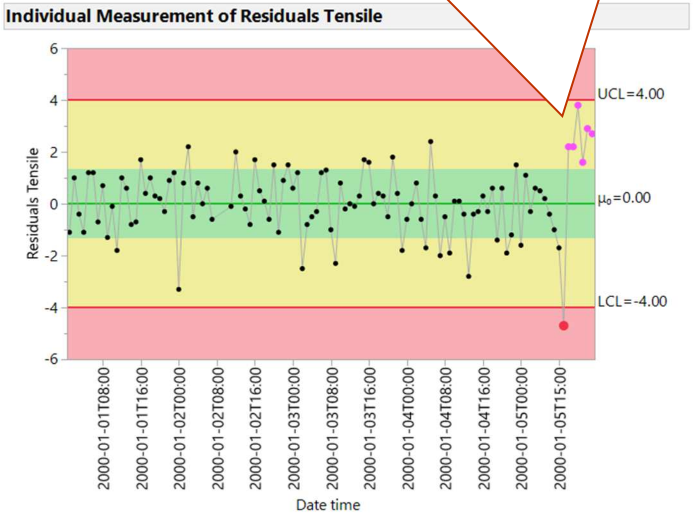
	Check 1	Check 2
Factor A	46.1	20
Factor B	4.49	3
Predicted tensile	54.7± 4	49.9 ± 4
« Real » tensile	53 	45.2 

The interval [45.9 ; 53.9] does not include the « real » value.
The soft sensor accuray or precision could have changed.
What is the cause?

1. Identify predictors → 2. Clean and screen data → 3. Select, train and validate model → 4. Monitor & adjust process based on predicted values → **5. Monitor model adequacy using residuals**

- It could be interesting to plot the residuals (Observed value – prediction) on a control chart to identify trends
- The error was stable for a significant period of time. The recent trend observed allowed to identify a new factor affecting tensile strength and add this factor to the model… We learned something on the process!

Even if the « real » tensile is within the control limits, a trend can be identified.
Finding the cause could allow to identify a new factor affecting tensile strength.

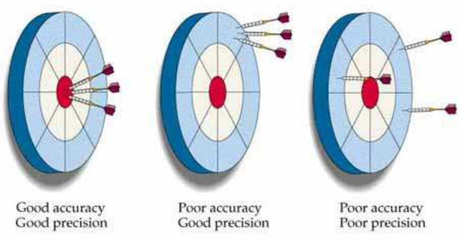


Note: Sigma was specified during launch.

Note: 3 samples were excluded.

Conclusion

- Today, it is not rare to have access to a large amount of process data that could allow to build a good model (a soft sensor) to predict a costly quality test



- However, one must make sure the soft sensor will be reliable enough to have an acceptable risk of drawing a bad conclusion based on its prediction

- A good soft sensor can be a catalyst to learn about the factors affecting a quality parameter.

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