
AICHELIN Multipurpose chamber furnace line

# Predictive maintenance for heat treatment plants – Part 2

Veröffentlicht am 11. Oktober 2021


Hartmut Steck-Winter
Engineer, Ph.D, Senior Adviser, Amateur Philosopher


**#AICHELIN**, **#ConditionMonitoring**, **#HeatTreatment**, **#Instandhaltungssoftware**, **#jakob**, **#Maintenance**, **#MaintenanceManagement**, **#PredictiveMaintenance**, **#Prozesswärme**, **#SmartMaintenance**, **#Thermoprozess**, **#Thermoprozesstechnik**

In the second part of our article about Predictive Maintenance for heat treatment plants in **Prozesswärme 05 2021** we report on our newly developed Remaining Useful Life (RUL) forecast method.

A RUL forecast can support periodic and condition based preventive maintenance in deciding whether a failure-critical component can continue to be used or whether it should be replaced preventive because the risk of a failure becomes too great.

We followed two approaches during development. The first RUL forecast method developed under the direction of Fraunhofer Austria Research is implemented in the mobile maintenance assistant #jakob. The probability of survival is calculated and visualized on the basis of statistical Weibull service life data, influence factors and the operation time.

In addition to the parameters in the aforementioned version, the second method also takes the strong correlation between the probability of failure and the wear reserve of a component into account. The wear condition is determined during a guided inspection. That is what this technical report is about.

It should answer the following questions:

- Why do we need a special RUL forecast method for heat treatment plants?
- What exactly should be achieved with a RUL forecast?
- What role do statistical service life data and dynamic influence factors play?
- Why are operator-guided wear condition assessments so important?
- And last but not least: How can we continuously improve a RUL forecast and the underlying data?

Heat treatment plants or similar thermoprocessing equipment are not just slightly warmer machines. Hence there are particular maintenance challenges: Almost all failure-critical parts are built into the hot zones. In the hot zones itself, classic condition monitoring (CM) is not possible due to the high temperatures or the surrounding atmosphere. In addition, because of the very long repair times caused by the cooling and reheating of the hot zones, unplanned, short-term inspections are also not advisable. Owing to the very high consequences of failure, they must be prevented by almost all means.

"Standard Predictive Maintenance" (PdM) concepts for machines - mostly Artificial Intelligence (AI) supported sensor based anomaly detection along with flexible service intervals - cannot be transferred to the core areas of heat treatment plants. Therefore, maintenance technicians have to substitute condition sensors in the hot zones, so to speak. Standard PdM must hence be adapted to the specific needs.

A planned annual maintenance break is the only possibility for an inspection and if necessary the preventive replacement of the failure-critical components. In other words - preferably before, but at the latest during an annual maintenance break - maintenance professionals must assess whether a failure-critical component will surely survive at least until the next planned maintenance break. The forecast horizon must therefore cover the very long period between two annual maintenance breaks, usually around one year. A really difficult task, today even without technical assistance systems!

## Anomaly detection

As we explained in the first part of our report in **PROZESSWÄRME 07 - 2020**, anomaly detection to reduce the consequences of failure also noticeable a few days to hours before a failure. Hence anomaly detection does not solve the inevitable problem with the long-time interval between two annual maintenance breaks. Anomaly detection alone cannot replace a condition assessments during an inspection. Without some additional condition assessments of the failure-critical components by maintenance professionals, any RUL prognosis will come to nothing!

## Basis and hypotheses

The new RUL forecast method is based on a number of hypotheses:

- Maintenance is always carried out on the components of an assembly. Components are the unit of consideration of the three preventive maintenance strategies periodic, condition-based or predictive.
- The wear reserve (Abnutzungsvorrat) of a component correlates strongly with its RUL.
- The wear degradation curve correlates sufficiently with the survival probability or with the Weibull form factor. It provides information about the expected value of wear at any point in time.
- The consequences of failure correlate strongly with the permissible failure probability.
- Influence factors (Einflussfaktoren) shorten or lengthen the "normal RUL" which only applies to reference conditions.
- The wear degradation curve and condition assessments from maintenance professionals must check each other for plausibility.

prognosis.

- ...

## Elements of a RUL forecast

The newly developed RUL prognosis is based on three pillars: (1) Weibull statistical lifetime data, (2) influence factors that can be measured as environmental or process data and (3) the real condition assessment of wear by maintenance professionals during a guided inspection. In a further development step in the future, anomaly detection could be integrated as a fourth pillar.

Figuratively speaking, the three pillars rest on a foundation with parts master data and the maintenance plan. Together they carry the RUL prognosis algorithm. The aforementioned components are continuously improved in a control loop.

### (1) Weibull lifetime data

The starting point for the RUL forecast are the Weibull parameters, characteristic service life (T), form factor (b) and operating time (t). In addition, there is the permissible failure probability (Bx) to be taken into account. The lower the characteristic service life and / or the permissible failure probability, the lower the RUL starting value. But the form factor also has a big impact. Operating time or cycles are subtracted from the RUL start value (TBx), just like with a backward-running stopwatch

### (2) Influence factors

All components are subject to location-dependent influence factors during their use. They shorten or lengthen the "normal service life", best be described as the "normal typical use" of a component.

In practice it has been shown that influence factors can have a very drastic effect on the RUL. The effect of the influence factors can be illustrated with a motor vehicle maintenance display. While in older vehicles only the distance driven (i.e. the use) played a role for the next maintenance, today dynamic factors recorded by sensors, such as driving style, also have an influence. A RUL calculation with influence factors is therefore more realistic. Influence factors are recorded utilizing the AICHELIN process monitoring system FOCOS.

### (3) Wear condition assessment feedback from maintenance professionals

A RUL forecast is not just a math problem, rather the opposite. The active involvement of maintenance professionals in assessing the wear condition of the failure-critical components is of paramount importance. Without suitable feedback on the components condition, any RUL prognosis will come to nothing. Such feedbacks are the "calibration weights" of the statistical service life data and the influencing factors.

Regular status assessments on the wear condition of a component are usually given during an annual maintenance. Appropriate wear condition assessments feedback must be digitized, comprehensible, and ideally operator-guided with a technical assistance system supported component-specific checklists. The closer to reality and more detailed the wear condition assessment, the better the later quality of the RUL prognosis. Even maintenance professionals should not just rely on gut instinct.

## Expert cockpit: Wear reserve and RUL vs. Operating time

The expert cockpit displays - by the example of a component with an assumed permissible service life of 7.1 years - how the RUL of a failure-critical component is calculated from different perspectives:

- Left vertical axis: Wear reserve in % [Abnutzungsvorrat]
- Right vertical axis: RUL in years [Jahre]
- Horizontal axis: Operating time [Nutzungszeit] (t) in years [Jahre]
- Gray line [AV-RUL PER]: Wear reserve vs. RUL with linear degradation, but without influencing factors. Typically used for periodic maintenance of electronic components.
- Red line [AV-RUL EF]: Wear reserve vs. RUL with linear degradation and average influencing factors. Typically used for periodic maintenance of mechanical components.
- Purple curve [AV-Deg Exp]: Wear reserve vs. RUL with exponential degradation and average influencing factors. Typically used for condition-based maintenance.
- Green curve [AV-RUL RM Akt]: wear reserve vs. RUL with exponential degradation, wear condition assessment feedback and average influence factors.
- Colored points on the green curve [RM-AV]: Wear condition assessments. Each dot color corresponds to a specific wear reserve stock.
- Green dashed curves [AV-RUL EF Min/Max]: RUL variation with minimum and maximum influence factors.

- Brown double vertical line [RUL RM AVG]: RUL forecast up to the wear reserve limit.

- Black vertical line [t Akt]: Current operating time.

For many mechanical components the degradation is not linearly, but exponentially with the operating time. Due to the exponential growth of the degradation, the wear reserve is reduced much faster at the end of the expected useful life.

Of course, the expert view explained here is only one of several options. For example, just the RUL together with the probability of survival can be shown on a simple digital display.

## Benefit versus effort

An obvious benefit of a RUL prognosis system is the support of annual periodic or condition based preventive maintenance and spare parts requirement planning. For example, the method can provide a listing of all failure-critical components together with RUL forecast, failure probability, etc. With a mobile version, condition assessments can be operator-guided and made on the spot.

Unfortunately, it is a bit more difficult to weigh the benefit versus the effort, because the ROI is difficult to prove due to the prevention paradox. Nevertheless, the economic added value is one of the most important reasons for all PdM applications. From an economic point of view, PdM is always about improving technical availability while lowering maintenance costs at the same time. Ultimately, there is no question that even a single prevented failure more than justifies an investment in predictive maintenance.

An annual maintenance break is usually the only option for an inspection or the replacement of failure-critical components in hot zones without the system having to be taken out of service unplanned. This means that the time horizon of a supporting RUL forecast must be at least one year. The method described here has been developed for precisely this requirement.

AI does not yet play a major role in condition assessments and RUL forecasts. It is obvious to use the camera of a smartphone or a pad together with AI to record and assess the state of wear. Whatever, it should not be forgotten that AI needs a lot of learning examples in order to recognize a wear pattern. Today we are still miles away from that. In future however, AI will enable a quantum leap in a wear condition assessment.

So starting now is much more important than waiting for perfection. The transition between digitization and AI is fluid. Anyone who is moving in this direction now will not be left on the sidelines in the future and will be able to benefit from the further developments in predictive maintenance without too much additional effort.

## References

Steck-Winter, H.; Unger, G.: Vorausschauende Instandhaltung von Thermoprozessanlagen Praxisbericht Teil 1 – Anomalieerkennung, no. 07-2020, pp. 39-47, Prozesswärme, Vulkan Verlag, 2020

Steck-Winter, H.; Unger, G.: Vorausschauende Instandhaltung von Thermoprozessanlagen Praxisbericht Teil 2 – Restlebensdauerprognose, no. 05-2021, pp. 50-58, Prozesswärme, Vulkan Verlag, 2021