

# Development of Functional Requirements for Sustainable and Attractive European Rail Freight

## D5 – Defined threshold, pre-warning threshold and opening value

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## EXECUTIVE SUMMARY

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Condition Based and Predictive Maintenance will result in more and more accurate forecasts overtime, as big data turns to smart data, to be processed into advanced status warnings and allocated to the ideal maintenance shops. Condition Based and Predictive Maintenance means the integration of condition monitoring into maintenance and fleet control by capturing data, deriving live forecasts of components and system behavior and enhancing underlying algorithms for root cause analysis.

Beyond the intelligence of system functions, i.e., recognition of patterns and neural prognostics, the core innovation of Condition Based and Predictive Maintenance takes place at the process level. This includes new roles and responsibilities in the interaction of the areas asset, fleet and maintenance management, but also new forms of collaboration with regulative authorities that need to approve of data based dynamic changes to technical threshold values (part of the next deliverable).

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## ABBREVIATIONS AND ACRONYMS

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CBM	condition based maintenance
EDX	energy dispersive X-ray spectroscopy
NN	neutralization number
PCB	printed circuit board
SEM	scanning electron microscopy
SMD	surface mounted device
TBN	total base number

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## 1. INTRODUCTION

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Digital developments like the 'Internet of Things' and 'Big Data' require a change in the usage and handling of data as the volume of data is increased tremendously. A lot of new data has already been generated and more new data sources are expected to be created in the future years. Taking into account that more data is needed as a basis as it has been before, it is obvious that more data needs to be handled and processed.

Further, the identified thresholds describe as the state of art the development of a Condition Based and Predictive Maintenance program that is focused and based on specific locomotives and respective components.

The major outcome of the data handling and the data analysis are these variables and thresholds which are representing the condition of the respective components as well as the aligned tasks being important within the following maintenance.

Generally, the analysis of data is most efficient when developing an end-to-end condition based and predictive maintenance process. With the at hand concept, the volume of data has highly increased.

## **2. CONDITION BASED MAINTENANCE OF DIESEL LOCOMOTIVE ENGINES**

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### **2.1 TASKS AND OBJECTIVES**

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Condition based maintenance (CBM) provides economic and ecologic advantages. One critical component of a diesel locomotive also needing maintenance is the engine. Thereby, the condition of the engine oil provides information about the condition of the oil and the engine itself. In this chapter, the relevant signal(s) that can be provided by a sensor system for CBM of a diesel locomotive engine are reported.

The aim of this work is to provide an online oil condition monitoring system considered for the operation in a diesel locomotive (shunting locomotive). In the first step, an in-depth system analysis delivered critical parameters to be monitored. Based on these findings, the usefulness of the sensor concepts was confirmed in laboratory experiments. After validation in the laboratory, fabricated prototypes are currently prepared for field tests.

This deliverable presents the status on the laboratory evaluation process and summarizes the design of the sensor system.

### **2.2 SYSTEM ANALYSIS**

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System analysis was performed to identify the critical oil condition stages during operation in a diesel locomotive engine. Therefore, several oil samples were taken from various locomotives and analysed in the laboratory at AC2T research GmbH. The analyses comprised viscosity measurements, acidity and basicity analyses, oxidation and in particular elemental composition. The latter is relevant for the condition of the engine (parts). Besides “normal” degradation showing, e.g., increase in acidification, some oil samples were characterized by an elevated amount of copper in the oil.

As next step, the origin of the copper in the oil was investigated. Therefore, the particles in the oil were separated by filtration and centrifugation. Particles extracted were analysed using scanning electron microscopy (SEM) with energy dispersive X-ray spectroscopy (EDX) to document the shape and composition of the particles. Although found in relevant amounts, these analyses did not provide a significant hint to the presence of copper particles.

Consequently, it was concluded that copper in oil can be attributed to corrosive attack of the oil to copper parts of the engine.

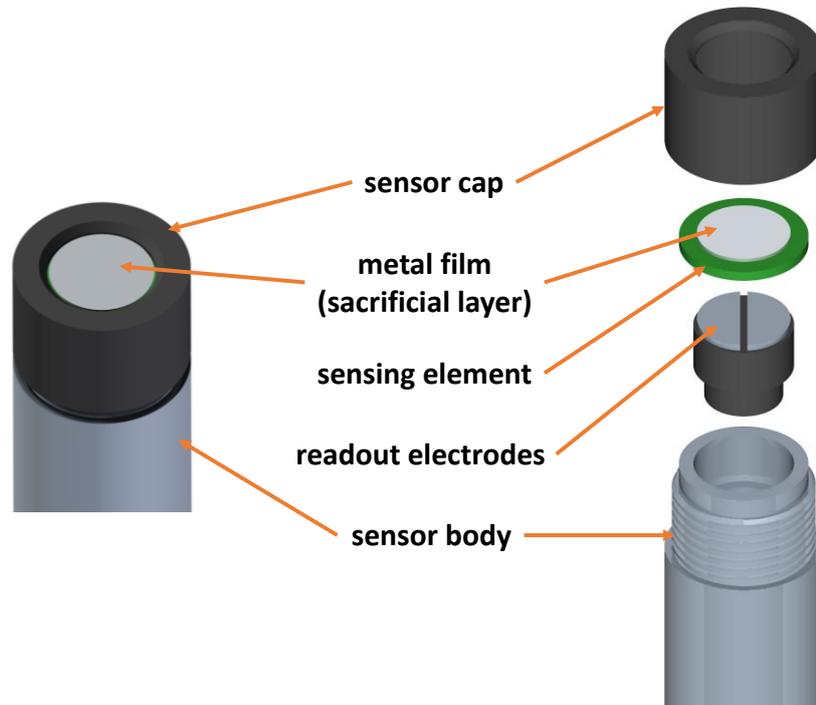
Having identified corrosion as an additional indicator causing an oil change, a sensor system should be able to monitor, among others, the corrosiveness of the engine oil. Therefore, the key element of such sensor system should be based on the corrosion sensor as reported in [1, 2].

### **2.3 PRE-EVALUATION OF A SENSOR SYSTEM FOR DIESEL LOCOS**

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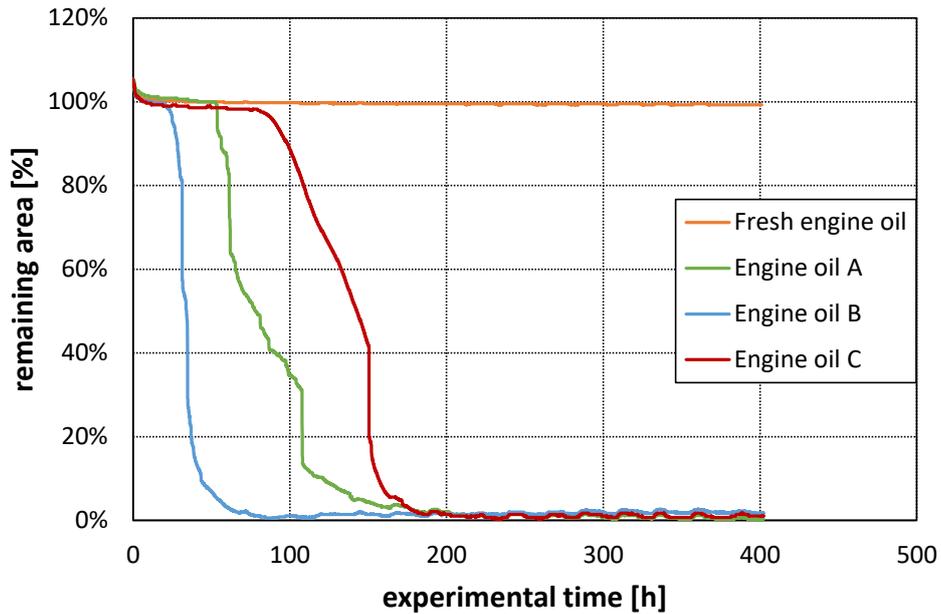
In order to elaborate the degree of corrosiveness of the used engine oils, defined pieces of a copper wire were immersed in selected oils. This setup was then kept in an oven for a defined time period of 60 h at a defined temperature of 100 °C. Afterwards, the copper content of the oils was determined. Depending on the oil condition, some of the oils showed a significant increase of copper after the experiment. Consequently, these oils have been described as corrosive against copper.

Based on these findings, static corrosion tests were performed using the proposed corrosion sensor setup from [1, 2] as shown Figure 1. The concept of the corrosion sensor is based on the removal of a thin metal film once exposed to oils with a critical degree of corrosiveness. Accordingly, this metal film serves as sacrificial layer. For these tests, copper and lead films were used as sacrificial layers. The metal film is part of the sensing element being itself located between sensor cap and sensor body. The remaining area of the sacrificial layer is continuously monitored via readout electrodes.



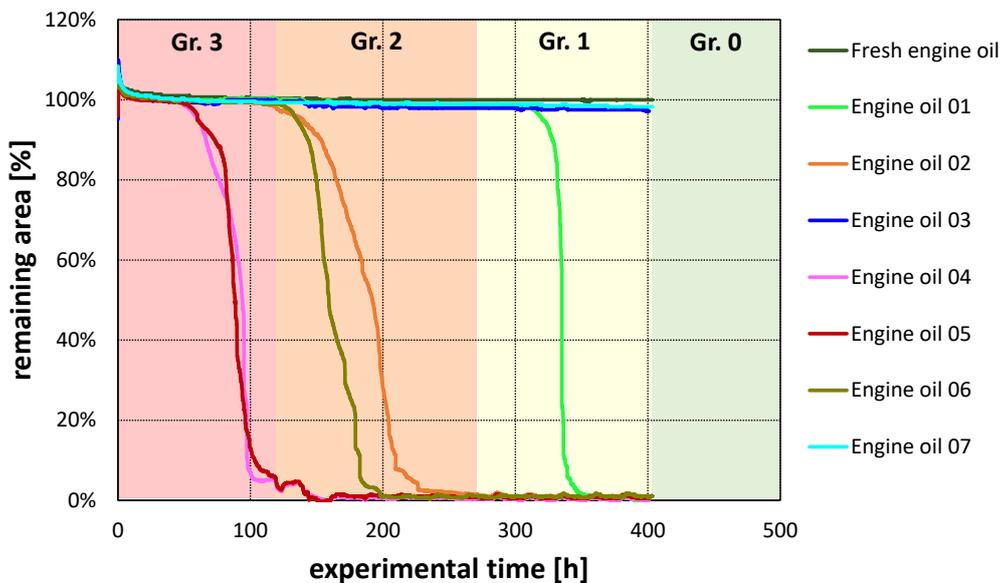
**Figure 1: Schematic setup of corrosion sensor including sensor body with readout electrodes, sensing element with sacrificial layer and sensor cap for fixation**

With the help of these tests, the design of the sensing element was optimized, in particular regarding the copper film thickness. The results in Figure 2 refer to tests with optimized film thickness. A corrosive attack is clearly noticeable by a sharp decrease of the signal for the remaining area of the sacrificial element thus indicating the removal of the copper film. The signal decrease is depending on the condition of the used engine oils. The curves shown were obtained with those engine oils that produced already significant amounts of copper in the copper wire immersion tests. As expected, the fresh oil showed no significant attack of the sacrificial layer.



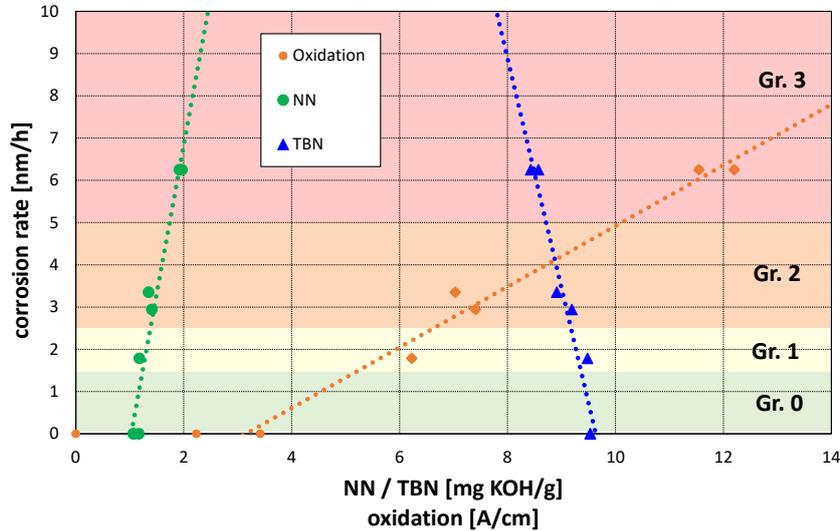
**Figure 2: Trends of corrosion sensor signals recorded in laboratory experiments using copper as sacrificial layer immersed in selected engine oils from a diesel locomotive**

Complementary, used engine oils were included using the corrosion sensor with lead as sacrificial layer as previous studies revealed good correlation to the oil condition [1, 2]. Figure 3 shows the results with oils that showed by copper corrosive attack. The degree of corrosiveness ranges from non-corrosive behaviour (Group 0, referring to good condition) to highly corrosive behaviour (Group 3, referring to bad condition).



**Figure 3: Trends of corrosion sensor signals recorded at laboratory experiments using lead as sacrificial layer immersed in selected engine oils from a diesel locomotive. Coloured background indicates the classification in four corrosion groups: Group 0 – no corrosive attack; Group 1 – slight corrosive attack; Group 2 – medium corrosive attack; Group 3 – severe corrosive attack**

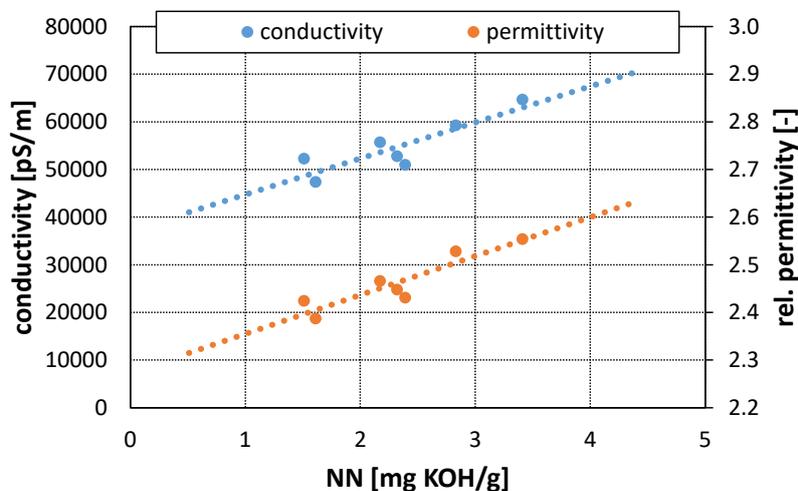
The calculated corrosion rate out of the experiments shown in Figure 3 could be well correlated to the oil condition of the oil samples expressed by the neutralisation number NN, total base number TBN or oxidation as can be seen in Figure 4. The corrosion rate is calculated by dividing the thickness of the sacrificial layer by the time needed for corrosion of this layer.



**Figure 4: Correlation between corrosion rate of lead (corrosion sensor experiments) and oil condition of the used engine oils (neutralisation number NN, total base number TBN and oxidation).**

**Coloured background indicates the classification in four corrosion groups:  
 Group 0 – no corrosive attack; Group 1 – slight corrosive attack  
 Group 2 – medium corrosive attack; Group 3 – severe corrosive attack**

As additional sensor elements, electrical parameters such as conductivity and relative permittivity were evaluated using selected used engine oil samples. Thereby, the conductivity and relative permittivity of the oils were measured and correlated to the oil condition as exemplary shown in Figure 5 for the neutralisation number NN. Conductivity and relative permittivity are increasing with increasing acidification, thus these parameters can be included in CBM.



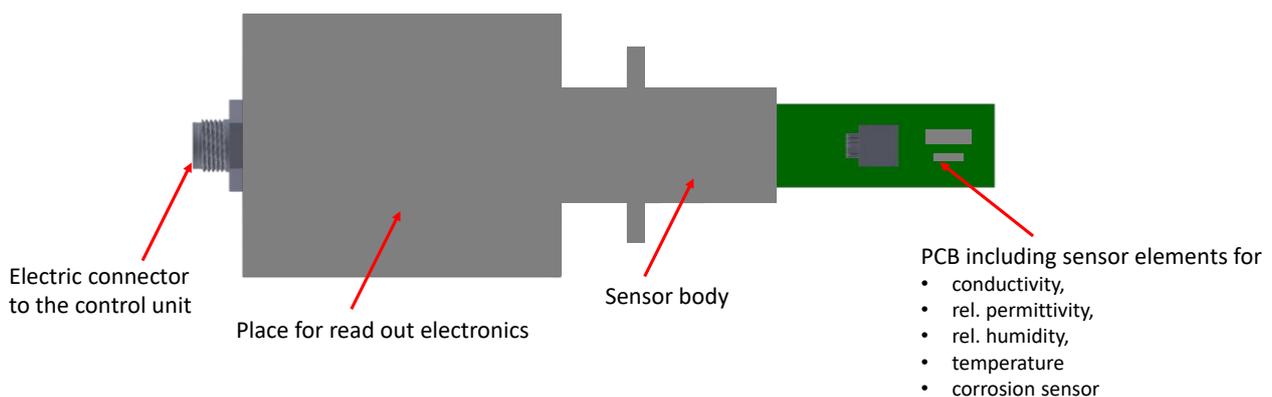
**Figure 5: Correlation between electrical oil parameters (conductivity and relative permittivity) and oil condition expressed by neutralisation number NN**

## 2.4 SENSOR DESIGN AND COMPILATION

Typically, several sensors are assembled for a sensor-based CBM of lubricated systems. Beside the corrosion sensor, further sensor types were implemented in the sensor system able to measure electrical parameters (conductivity and permittivity), relative humidity, and oil temperature. Conductivity and permittivity are sum parameters of the oil condition, relative humidity is a measure for the water content and therefore an indicator for contamination with water. Oil temperature is mainly needed for compensation of temperature effects of the other measurement concepts.

The design provides sensor elements that are all mounted on a printer circuit board (PCB) which is in contact with the oil. The PCB is integrated into the sensor body and internally connected to the read-out electronics as can be seen in Figure 6.

The sensor element for conductivity and permittivity is fabricated directly onto the PCB. For relative humidity, a capacitive humidity sensor for oil humidity measurement is used. A PT1000 sensor is used for temperature measurement. The sensing element for the corrosion sensor is fabricated onto a separate PCB (not shown in Figure 6) which is connected via a board-to-board connector.



**Figure 6: Sensor setup**

The ongoing work comprises the finalisation of the sensor design, especially the dimensions of each sensor component for the proper implementation in the diesel locomotive engine. After validation in the laboratory by simulation of critical engine (oil) conditions, prototypes will be fabricated and equipped with a pre-algorithm. In 2019, field tests will be performed for the evaluation under real operating conditions. Signal data generated will be evaluated for integration in CBM of diesel locomotives.

## 2.5 BASIC THRESHOLDS AND PRE-WARNING THRESHOLDS

Based on the laboratory experiments, basic thresholds and pre-warning thresholds were defined for the developed multi-sensor system used for the monitoring of engine oils in diesel locomotives (Table 1). For this monitoring system, no opening values are considered as trends (progress over time) are more expressive and reliable compared to absolute values. Therefore, the basic algorithm only evaluates sensor signal increase or decrease.

In detail, the relationships between relevant variables (see also 2.2) and basic thresholds as well as pre-warning thresholds derived from laboratory experiments are described as follows:

- **Corrosion:** This parameter describes the corrosiveness of the engine oil. Depending on the sensor design, the sensor response is adjusted to different levels of corrosiveness mainly defined by the type and amount of acidic compounds. As there is a steep signal decrease once the threshold corrosiveness is approached (see Figure 3), the threshold and pre-warning threshold are set at high values of remaining area.
- **Electrical conductivity:** This parameter describes the general oil condition (additive depletion, base oil oxidation, contamination). The threshold and pre-warning threshold are set based on those defined for comparable large engines and confirmed by analyses of engine oil samples from diesel locomotives.
- **Relative permittivity:** This parameter is determined to monitor the oil's polarity. Thus, it delivers information about the oil condition (oxidation, contamination with polar agents), which is complementary to the electrical conductivity. The threshold and pre-warning threshold are set in a similar way as the electrical conductivity.
- **Relative humidity:** This value is a measure for the dissolved water in the oil. As long as the water remains dissolved, no significant impact on the lubrication performance is to expect. With increasing relative humidity, the risk of free water increases. Therefore, the threshold and the pre-warning threshold are basically set to 80% and 60%, respectively.
- **Temperature:** Temperature is measured to compensate the temperature dependence of the sensor signals. Temperature compensation accounts for the operation of the locomotive (operation, downtime, seasons, etc.). Temperature is currently only recorded, therefore no thresholds are defined as oil temperature is a parameter commonly captured by other monitoring systems.

The thresholds and pre-warning thresholds will be refined and validated during the field test performed in Fr8Rail II to IV.

Parameter	Measurement range	Threshold	Pre-warning threshold
Remaining area for corrosion	100 to 0 %	50%	70%
El. conductivity	0 to 500 nS/cm	Increase of 50%	Increase of 40%
Rel. permittivity	1 to 5	Increase of 10%	Increase of 7%
Rel. humidity	0 to 100%	80%	60%
Temperature	-20 to 120°C	-	-

**Table 1: List of basic thresholds for sensor signals obtained by the multi-sensor monitoring system**

## 2.6 FEASIBILITY AND BENEFITS

The fundamental feasibility has been proven by laboratory tests (see 2.1). Functionality of the completed multi-sensor monitoring system was confirmed by laboratory-based simulation of entire oil change intervals (Fr8Rail II WP8). Reliability under real application conditions is being evaluated with three systems installed in diesel locomotives of DB (Fr8Rail III). Comprehensive evaluation of

functionality, expressiveness of data gained, reliability and efficiency against cost of detection is planned in Fr8Rail IV.

### **3. CONDITION BASED MAINTENANCE OF ELECTRIC LOCOMOTIVE**

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#### **3.1 ANALYSE BIG DATA**

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The first data analyses to define thresholds focused on specific electronic locomotives and diesel locomotives. One of the major and essential tasks in the condition-based and predictive maintenance project is the determination of those variables which assess the condition of a component (condition or reference variables, such as temperature, wear and condition of operating material), as well as the determination of the threshold of these reference variables in which a maintenance task is required. Availability and appropriateness of variables by existing was evaluated for condition-based and predictive maintenance. To determine the status and monitoring parameters (reference variables) a substantive data analysis about the components is essential to gain detailed and deep knowledge about the lifecycle of each component. The outcome will be detailed knowledge about the operational behaviour of these components. This analysis and knowledge was carried out in the CBM concept on two different ways:

1. Using Big Data Analytics: by combining IT experts for deep learning algorithms and locomotive engineering know-how to interpret the data analysis in order to identify patterns and thresholds which assess the actual condition. We therefore identified
  - a. Minimum values
  - b. Maximum values
  - c. Average values
  - d. Median values
  - e. standard deviation
  - f. 5% Quantil values
  - g. 95 Quantil values
2. Involve engineering experts for the relevant components e.g. subsystem manufacturer to develop a CBM based maintenance program.

The initial definition of thresholds for the failure / maintenance modes of a specific component was done by the IT and analytics experts. In cooperation with the engineering experts, the operator was able to review and identify these thresholds by assessing the results of component analysis.

In the next step, the results will feed back into the maintenance documentation of the operator, being responsible for a component. Furthermore, it can ensure proper usage of the jointly gained experience even for future component and vehicle developments and concepts.

### 3.2 DETERMINATION OF THRESHOLDS FOR TEMPERATURE SIGNALS

As shown in the table below, we defined several thresholds for a bundle of signals which are currently available on the locomotive. We focused on thresholds which are correlating with temperature – with these thresholds we support the monitoring and the evaluation of

- Power converter 1 and 2
- Traction motor
- Traction motor bearing, and
- Auxiliary converters

NameVar	min	max	Durch	Media	Stan	q05	q95	Antei	Grenzwert
Temperatur_ZSG2	-122,57	65,5143	24,429	22,5786	10,18	11,02	46,7	0,5381	46,7
Temperatur_ZSG1	-9,4531	65,3556	24,455	22,5786	10,21	10,86	46,83	0,5381	46,8
Temperatur_Trafo_Kreis2	-10,609	72,8365	25,796	23,7121	11,39	11,02	51,46	0,5929	51,5
Temperatur_Trafo_Kreis1	-9,2037	68,824	25,932	24,0748	11,22	11,24	51,14	0,5929	51,1
Temperatur_Stromrichter_2	-10,745	47,5149	21,841	20,6064	8,944	8,977	40,56	0,5929	40,6
Temperatur_Stromrichter_1	-9,7025	51,822	22,017	20,9464	8,998	9,113	40,71	0,5929	40,7
Temperatur_Lager_FM4_DG2	-742,83	742,782	30,605	50,1445	283,6	-565	580,5	1,238	580,5
Temperatur_Lager_FM3_DG2	-10,065	105,594	23,617	15,3471	25,98	0	68,82	1,238	68,8
Temperatur_Lager_FM2_DG1	-11,561	675,386	26,501	16,9113	28,3	0	72,47	1,238	72,5
Temperatur_Lager_FM1_DG1	-742,83	742,782	30,402	50,1445	283,5	-566	578,7	1,238	578,7
Temperatur_im_ASG2	-8,5917	66,9424	26,189	24,6869	10,28	12,22	48,81	0,5381	48,8
Temperatur_im_ASG1	-6,7781	67,1691	26,328	24,8456	10,28	12,38	48,65	0,5381	48,6
Temperatur_FM4_DG2	-742,83	742,782	39,69	64,1088	285,7	-566	580,5	1,238	580,5
Temperatur_FM3_DG2	-10,247	344,528	36,724	16,2539	42,4	0	110,8	1,238	110,8
Temperatur_FM2_DG1	-9,2037	681,28	59,924	59,8016	30,6	12,79	110,8	1,238	110,8
Temperatur_FM1_DG1	-9,7025	193,029	59,798	60,1417	30,95	11,56	111,2	1,238	111,2
HBU2_Temperatur_PWR2	-15,959	76,7734	14,894	14,2665	7,389	3,99	27,81	0,5929	27,8
HBU2_Temperatur_PWR1	-15,596	91,2817	16,418	15,7174	8,008	4,836	29,86	0,5929	29,9
HBU2_Temperatur_EST	-16,443	94,0625	16,869	16,0801	8,121	5,199	30,71	0,5929	30,7
HBU2_Temperatur_4_SIBCOS	-8,1005	61,7814	23,706	23,697	6,539	13,18	34,22	0,5381	34,2
HBU2_Temperatur_3_SIBCOS	-7,8587	61,7814	20,619	20,3117	6,777	10,03	32,16	0,5381	32,2
HBU2_Temperatur_2_SIBCOS	-12,937	49,3284	15,569	15,3547	6,735	5,32	26,84	0,5381	26,8
HBU2_Temperatur_1_SIBCOS	-0,6045	53,6809	29,64	29,7421	5,951	19,71	39,17	0,5381	39,2
HBU1_Temperatur_PWR2	-18,377	65,6503	18,873	18,1354	7,954	7,254	33,37	0,5929	33,4
HBU1_Temperatur_PWR1	-18,982	63,8367	17,451	16,9264	7,642	5,682	31,19	0,5929	31,2
HBU1_Temperatur_EST	-20,191	93,2162	19,9	19,1027	8,644	7,375	35,18	0,5929	35,2
HBU1_Temperatur_4_SIBCOS	-7,2542	61,7814	21,612	21,3998	6,752	11,36	32,28	0,5381	32,3
HBU1_Temperatur_3_SIBCOS	-6,5288	61,7814	20,684	20,4326	6,684	10,28	32,28	0,5381	32,3
HBU1_Temperatur_2_SIBCOS	-11,969	66,1339	15,758	15,3547	7,009	5,199	28,05	0,5381	28,0
HBU1_Temperatur_1_SIBCOS	-2,0553	55,8572	27,378	27,445	6,29	17,29	37,36	0,5381	37,4

Table 2: List of thresholds for several signals

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- [2] Schneidhofer C., Dorfmeister M., Dörr N.: In-line corrosion sensor for oil condition monitoring of biogas operated stationary engines, T & S (Tribol. Schmierungstech.), Vol 3/2016, p 31-37, expert Verlag, ISSN 0724-3472, 2016