Paris Session 2022

For power system expertise

RELIABILITY ENHANCEMENT THROUGH MACHINE LEARNING COMBINED WITH ADVANCED DIGITAL METHODS FOR TRANSFORMERS AND REACTORS

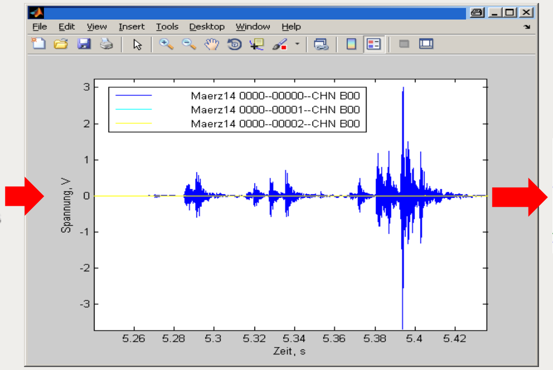
SC B5 / PS3: Integration of Intelligence on Substations

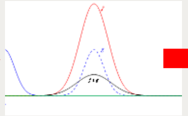
Q3.1

Karsten Viereck (Germany)

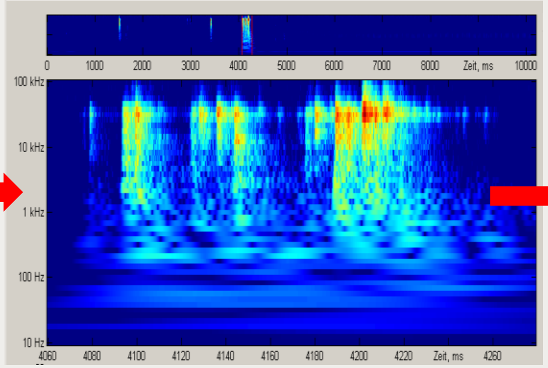
I. Benefits of digital solutions like machine learning, artificial intelligence

250 Mvar VSR, 440 kV, acceleration sensor on tap-changer head cover

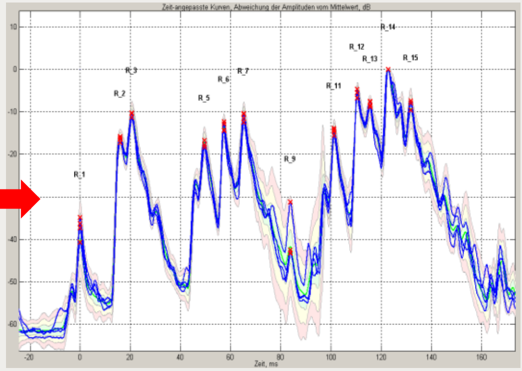




Wavelet - Transformation and filtering,
Convolution with a Gaussian-Function



Time frequency representation

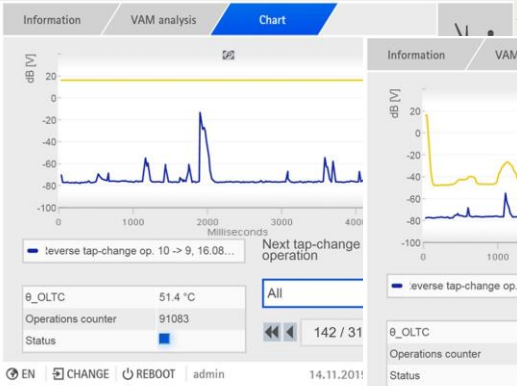


Peak detection and pattern recognition

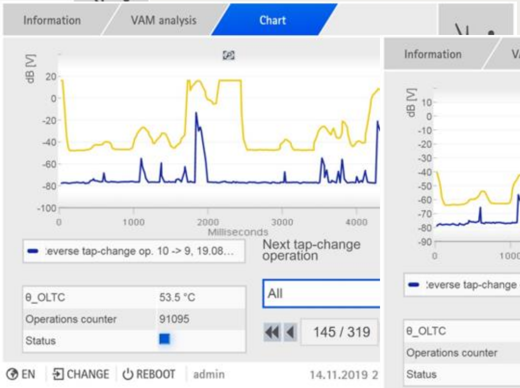
Machine learning as an efficient method for online monitoring of operating equipment

Limit curve

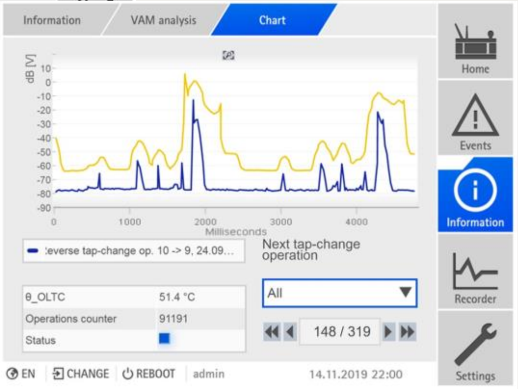
Envelope
Vibration signal



Flat line: System starts learning process



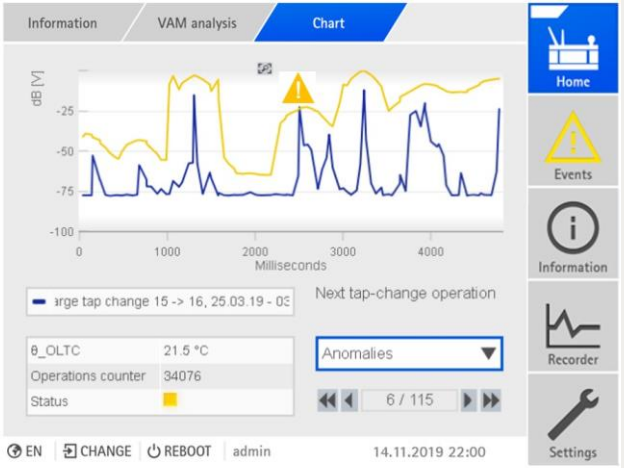
Acoustic envelop after three OLTC operations per tap-changer position



Acoustic envelop after five OLTC operations per tap-changer position, the system is now sufficiently trained to monitor the tap-changer

If a deviation in time or amplitude is detected, the monitoring system generates an alarm message

LN: SVBR;
data object:
VAM Anom Det



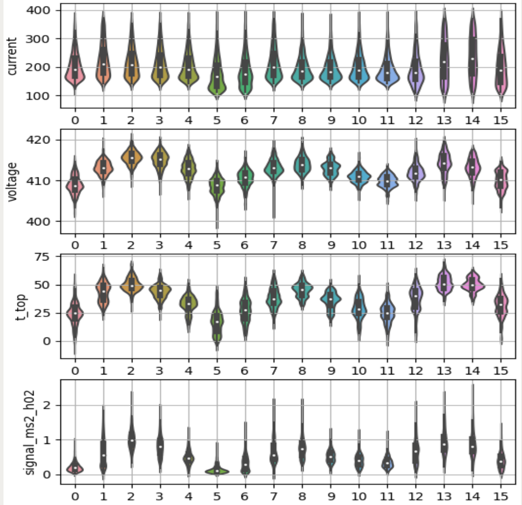
Group Discussion Meeting

II. Benefits of digital solutions for the equipment life cycle in substations

Application of a GREY BOX – Regression Model

For recalculation of vibration levels of selected harmonics in order to be able to detect changes in the active part of reactors / transformers

1. Vibroacoustic long-term Investigation on a 440 kV, 250 Mvar Variable Shunt Reactor



- Load current,
- Operating voltage
- Top oil temperature
- Vibration data
- Tap-changer position

Violin plot to represent the statistical distribution of data over three years of VSR operation (about 22.500 data points)

2. Verification of different Grey Box - Model Designs

Input variable, p				Model		
				COMPLEX	**LINEAR**	**LIN COMB**
Notation for the name of model				$F = \left\| \sum_i p_i \cdot (q_i + q_{(t)i} \cdot T) \right\|$	$F = \sum_i p_i \cdot (q_i + q_{(t)i} \cdot T)$	$F_i = p_i \cdot (q_i + q_{(t)i} \cdot T)$ $F = \sum_i a_i F_i$
i²	**ui**	**u²x**	**u²x²**			
Calculation formula				$q_i, q_{(t)i} \in \mathbb{C}$,	$q_i, q_{(t)i} \in \mathbb{R}$	$q_i, q_{(t)i} \in \mathbb{R}, \sum_i a_i = 1$
i^2	$u \cdot i$	u^2/x	u^2/x^2	$q_i, q_{(t)i} = \text{argmin}((F - v_{tank})^2)$	$q_i, q_{(t)i} = \text{argmin}((F - v_{tank})^2)$	$q_i, q_{(t)i} = \text{argmin}((F_i - v_{tank})^2)$ $a_i = \text{argmin}((F - v_{tank})^2)$
					Root Mean Square Error (RMSE)	
x	x			0.188	0.204	0.205
x		x		0.195	0.210	0.211
x			x	0.293	0.291	0.291
x		x	x	0.196	0.202	0.203

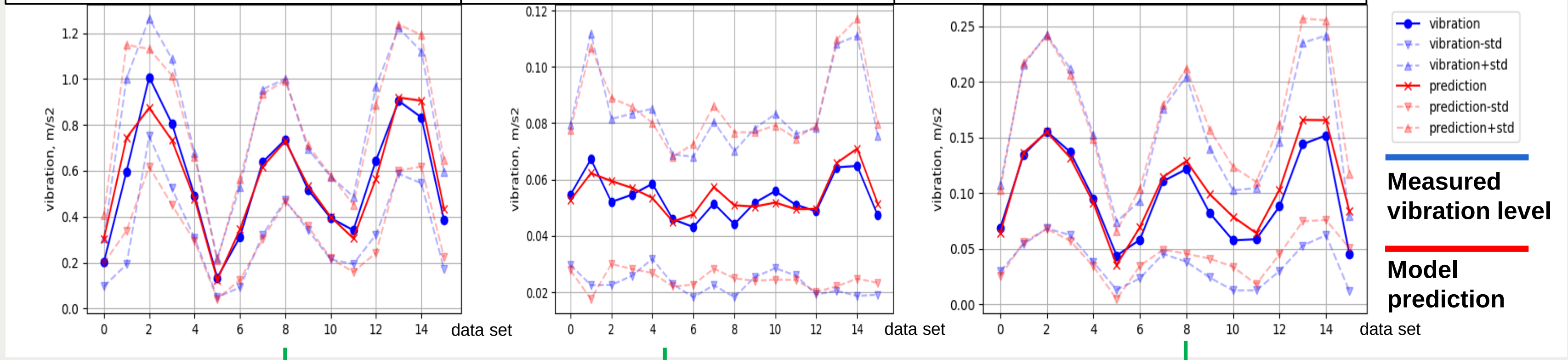
Parameter u²x² just to check the correct convergence of the model

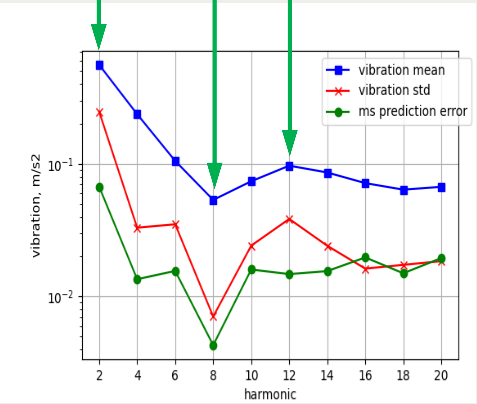
Selected regression model:
i²_ui_linear

II. Benefits of digital solutions for the equipment life cycle in substations

Discussion of reactor vibration prediction

Model i²_ui_linear, 2nd harmonic	Model: i²_ui_linear, 8th harmonic	Model: i²_ui_linear, 12th harmonic





Results over all recorded data sets

A large positive difference between the standard deviation and the RMS - prediction error indicates, that the model is good at predicting the existing changes in the vibration mean values

A small positive difference between the data mean value of the vibration and the standard deviation indicates that the vibration mean values are not constant and may depend on the input parameters (u, i, ϑ, n)

Conclusion

- ✓ Vibrations of a VSR can be reproduced by using a regression model
- ✓ Good conformity between the predicted and the measured values - no indication of a changed condition could be found
- ✓ Vibroacoustic analysis offers sufficient potential for the condition analysis
- ✓ Statistical data evaluation will be one of the essential features to characterise the operating condition and to create a new database for a digital asset management