Study Committee B5

Protection and Automation

PS3 Integration of Intelligence on Substations

Paper B5 - 11094 - 2022

RELIABILITY ENHANCEMENT THROUGH MACHINE LEARNING COMBINED WITH ADVANCED DIGITAL METHODS FOR THE PERFORMANCE EVALUATION OF TRANSFORMERS AND REACTORS

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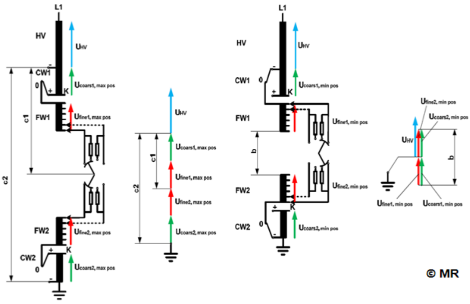
Motivation

- In the process of an On-Load Tap-Changer (OLTC) operation, the acoustic noise and the vibration pattern will reveal most of the mechanical or electrical events during the switching
- Considerable information concerning the OLTC operation can then be extracted from the vibro-acoustic pattern
- The information concerning the condition of shunt reactor operation can be also extracted from the vibroacoustic measurements

Objects of investigation

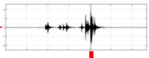


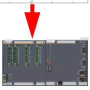
- State of the art design of variable shunt reactor with on-load tap-changers for wider regulation range of 80%
- 3x VACUTAP® VRG II 1302-245 tap-changer, Variable Shunt Reactor 250 Mvar, 440 kV

Approach and experimental setup

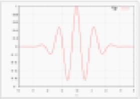
- Basic hardware design for online vibroacoustic investigation of tap-changer and reactor noise

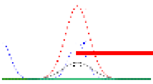
acceleration sensor on tap-changer head cover



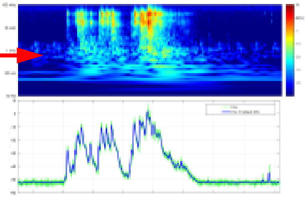


ISM controller hardware





Wavelet - Transformation and filtering
Convolution with a Gaussian-Function



- Vibroacoustic investigation to improve pattern recognition in the online process
- **Time frequency diagram** of a diverter switch operation and the matching of associated reference curves for pattern recognition

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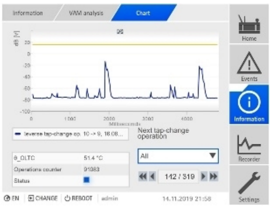
Self-learning online procedure for vibroacoustic tap-changer monitoring

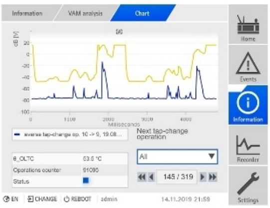
- The significant part of the data set for generating envelopes is reduced to about one hundred grid points during signal processing
- Assuming a Gaussian probability distribution for the signal level, the significant peaks of the recorded curve are subsequently expanded
- Through this procedure, the system iteratively learns during switching operations how the acoustic signature of a correctly functioning tap-changer looks like, this technique was labelled as the **Tracking Method.**
- With the self-created envelope, the system can check the course of all subsequent switching operations



- Autonomous creation of the limit value curve through a self-learning algorithm
- Learning phase approx. 5 switching operations per tap-changer position
- After five operations per tap, the system is sufficiently trained

Limit curve — Envelope vibration signal

Flat line: The vibroacoustic online monitoring system starts the learning process direct after initialization



Acoustic envelop after three OLTC operations per tap-changer position

- The system adapts to the down-calculated acoustic envelope through a continuously narrowing tolerance band

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

Event display yellow if the limit values are violated three times in a row

- Change in amplitude by more than 10dB or
- Change in timing by more than 300ms
- Event display gray when plausibility criteria are violated times (self-diagnosis)

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Transition to the Grey Box - Regression Model, Idea:

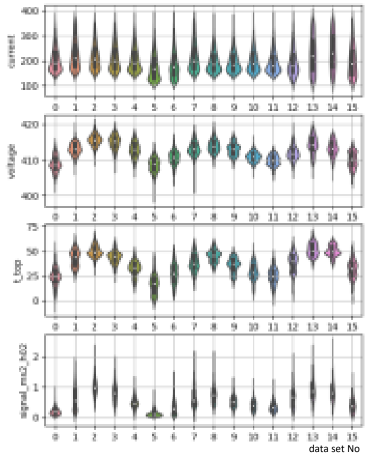
- During a **learning phase** (approx. 1 year) of the vibroacoustic monitoring system, the model was trained with measured vibration values and operating parameters of the transformer is quantitatively determined in the monitoring system
- In the **operating phase** (approx. 2 years) , the vibration is calculated from the transformer's operating data and compared with the measured values recorded by the online transformer monitoring system
- **A significant deviation may indicate a fault. A recognizable trend may indicate changes in the active part of transformer**

Input parameters for testing three different model approaches

- Load current, Phase 1U
- Operating voltage, Phase 1U
- Top oil temperature of the reactor
- Vibration data
- Tap-changer position

In 15 data sets over three years:

		Time frame	Number of data points
Year 1	0	-from 2017-11-16 to 2018-03-26	~2000
	1	-from 2018-03-26 to 2018-06-27	~2000
	2	-from 2018-06-27 to 2018-08-17	~2000
	3	-from 2018-08-17 to 2018-09-27	~2000
	4	-from 2018-09-27 to 2018-11-15	~2000
Year 2	5	-from 2018-11-15 to 2019-02-20	~2000
	6	-from 2019-02-20 to 2019-04-14	~2000
	7	-from 2019-04-14 to 2019-06-03	~2000
	8	-from 2019-07-12 to 2019-09-07	~800
	9	-from 2019-09-07 to 2019-10-27	~800
Year 3	10	-from 2019-10-27 to 2019-12-09	~800
	11	-from 2019-12-09 to 2020-01-27	~800
	12	-from 2020-01-27 to 2020-07-31	~800
	13	-from 2020-07-31 to 2020-09-12	~800
	14	-from 2020-09-12 to 2020-10-12	~800
	15	-from 2020-10-12 to 2021-01-18	~800



- Representation of the distributions of input data (current, voltage, top oil temperature) and the target variable a for each data set.
- The measurements cover a period of approx. 3 years.
The annual fluctuations are clearly visible

Verification of the Model Designs

Input variable, p				Model		
				COMPLEX	LINEAR	LIN COMB
Notation for the name of model				$F = \left\lvert \sum_i p_i \cdot (q_i + q_{(t)i} \cdot T) \right\rvert$ $q_i, q_{(t)i} \in \mathbb{C}$	$F = \sum_i p_i \cdot (q_i + q_{(t)i} \cdot T)$ $q_i, q_{(t)i} \in \mathbb{R}$	$F_i = p_i \cdot (q_i + q_{(t)i} \cdot T)$ $F = \sum_i a_i F_i$ $q_i, q_{(t)i} \in \mathbb{R}, \sum_i a_i = 1$
i²	ui	u²x	u²x²			
Calculation formula						
i^2	$u \cdot i$	u^2/x	u^2/x^2	$q_i, q_{(t)i} = \mathrm{argmin}((F - v_{tank})^2)$	$q_i, q_{(t)i} = \mathrm{argmin}((F - v_{tank})^2)$	$q_i, q_{(t)i} = \mathrm{argmin}((F_i - v_{tank})^2)$ $a_i = \mathrm{argmin}((F - v_{tank})^2)$
				Root Mean Square Error (RMSE)		
x	x			0.188	$\boxed{0.204}$	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 u^2x^2 just to check the correct convergence of the model

- The table shows a comparison of three models with different combinations of input parameters
- Each model was fitted to the same dataset. The measure for assessing the quality of the models is the mean square deviation of the acceleration prediction
- **Selected regression model:** **i²_ui_linear**

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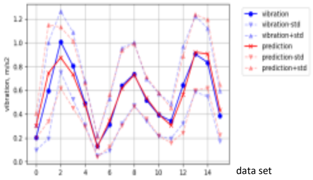
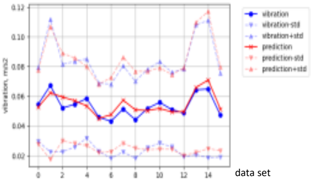
Discussion of reactor vibration prediction

Model: i²_ui_linear, 2nd harmonic



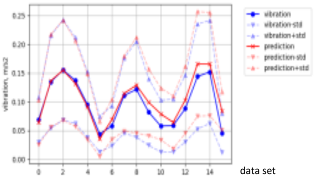
- Graphical representation of average values and standard deviations for the target variable vibration and calculated prediction
- The average values of the vibration signal for each data set can be predicted rather accurate. However, the model used alone cannot explain the high spread of single values of the vibration signal

Model: i²_ui_linear, 8th harmonic



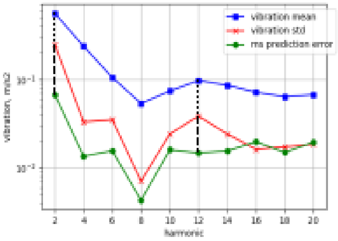
- Adequate predictability of the target variable vibration but simultaneously extremely low variance
- The seasonal fluctuations of the vibration signal in the diagram shown are less pronounced and hardly recognizable. However, relatively small discrepancies between the data sets can tend to be predicted by the model

Model: i²_ui_linear, 12th harmonic



- The higher harmonics can only be taken into account under certain assumptions. This mainly affects the excitation of the oscillation, because all harmonics have the same source
- Also in the 12th harmonic a very small difference between measured and predicted values for the target variable vibration despite the large variation of input variables

Conclusion



Results over all recorded data sets

- ✓ A <u>large positive difference</u> 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 <u>small positive difference</u> 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)

It has been demonstrated that the vibrations of a variable shunt reactor can be reproduced by using a regression model as well as operating data. The good conformity between the predicted and the measured values shows that no indication of a changed condition could be found. This confirms the very good operating condition of the variable shunt reactor again. Vibroacoustic analysis offers sufficient potential for the condition analysis of the active part of reactors and transformers.

In the future, statistical data evaluation will be one of the essential features that make it possible to characterise the operating condition of a transformer and to create a new database for a digital asset management.

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