ANOMALIES IN ON-LOAD TAP CHANGERS: FAILURE PREVENTION THROUGH CONTINUOUS MONITORING AND ADVANCED DATA ANALYSIS TECHNIQUES

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ABSTRACT

One of the leading causes of power transformer failures is the fault of the On-Load Tap Changer (OLTC) mechanism, mainly due to issues of dielectric, thermal or mechanical nature. Offline tests can assess the tap changer condition, in particular the Dynamic Resistance Measurements and DGA, but the results can be difficult to interpret, requiring expert analysis, in addition to the need for taking the transformer out of service.

Electricity North West (ENW) has run an Innovation project to maximize the use of existing assets. In particular, ENW has identified that there is a need for improving the management of repair, maintenance and replacement of OLTC in the distribution transformers.

Beside the conventional offline-tests it was decided to explore the capabilities of continuous on-line monitoring devices to find out leading indicators to properly plan maintenance and avoid catastrophic and dangerous failures. A project has started consisting of installing 42 permanent monitoring system collecting, continuously, parameters such as motor current, temperatures, transformer load, tap position and vibro-acoustic signature.

The raw data have been collected for months and analysed by both data scientists and transformer experts. The paper describes the results of the first data analysis, which show a potential in providing automated algorithms able to correlate a multitude of parameters, set automatically alarm thresholds and detect anomalies that need further investigation.

INTRODUCTION

Literature reports that around 40% of substation transformer failures are due to On-Load Tap Changer (OLTC) failures [1,2] caused by several reasons such as misalignment of contacts, poor design of the contacts, high loads, excessive number of tap changes, mechanical failures and coking caused by contact heating. The failure itself can be of mechanical (springs, bearings, shafts, and drive mechanisms) or electrical nature (coking of contacts, burning of transition resistors, insulation problems) [1].

Several parameters can be monitored on-line to provide an indication of the OLTC status. In particular:

- **Tap Position and Load:** recording the tap position along with the interrupted current and then performing statistics for each tap is useful to detect excessive wearing situations
- **Motor Current profile**: the initial current peak (within tens of ms) is in some way related to the static friction and backlash in the linkages. Sudden changes of this first peak can be cause of concern. The average current can also be evaluated, being related to the dynamic friction (mostly on OLTC where the motor directly drives the mechanical linkages)
- **Motor Current Index**: it is the area under the motor current curve and it summarizes the overall current profile, i.e. including the inrush, the average current and total running time. It can be expressed in Ampere-cycles or Ampere-seconds.
- **LTC Differential Temperature**: a significant increase of OLTC temperature over the main tank oil temperature could be cause of concern due to presence of abnormal sources of energy (losses due to bad contacts as an example).
- **Vibro-Acoustic Signature:** the mechanical movement of the tap changer produces vibrations that can be easily detected using proper sensors mounted on the OLTC tank walls. The acoustic signature can be recorded and compared with previous data under the assumption that for defect-free tap changers the acoustic signature is well repeatable in time. Differences of the acoustic profile in time should highlight the presence of anomalies. The acoustic signal can be split in two frequency bands: one in the range of few tens of kHz aimed at detecting problems of mechanical nature (e.g., excessive wear or ruptured springs) and one around 100 kHz aimed at detecting problems of electrical natures (arcing when there should not be any) [3-4].

Said that, there is no guideline or standard suggesting alarm thresholds on such parameters nor diagnostic guidance on how to interpret the changes over the time. The motor Current Index, as an example, can change on the same destination tap typically depending on the internal mechanical state determined by present and previous operation direction (UP-UP, UP-DOWN, DOWN-DOWN, DOWN-UP). The temperature parameters are also heavily dependent on ambient temperature, load and cooling status. For vibration signatures it is also highly possible that the signature is

different for every tap changer. So, how to set up alarms to detect anomalies?
ENW made 42 distribution transformers available for experimentation. The idea was to equip all the OLTC (all separate-tank type, connected on HV side) with sensors in order to monitor the above-mentioned parameters. The installation was done in 2017-2018 and, now, all the systems are sending raw data to a cloud securely hosted by CAMLIN Power. The data is now under analysis by a team of data scientists in order to detect correlations and anomalies using several and different mathematical approaches. The idea is to find out algorithms able to:

- Recognize a “normal” state by correlating all the monitored parameters
- Set adaptive thresholds around the normal state in order to detect anomalies

The OLTC diagnosis itself is not part of this first stage of the pilot, where the main focus is to detect differences between tap changers of same model or between operations of same tap changer. ENW will then follow up an investigation in the field using offline techniques to test the tap changers where the anomalies were detected and confirm if there is a defect and where it is located. This will then lead to the third stage which will be the correlation of the findings in the field with the data in order to provide diagnostic algorithms.

FIELD TRIAL

Table 1 reports a summary of monitored OLTC, while Figure 1 shows the monitoring system and the typical arrangement of the sensors.

Table 1 List of monitored OLTC

BRAND	TYPE	QUANTITY
AEI	3S21	5
AEI	M21	6
AEI	S21	2
ATL	AT316	1
English Electric	DIAL TYPE	3
Ferranti	DC3	4
Ferranti	DS2	9
Ferranti	FC4 / FC6	4
Fuller	HD314	2
Fuller	HD319	1
Fuller	HS319	5

Data collection is triggered by presence of motor current at each switch over operation. Raw sensor waveforms of acceleration and current (sampled synchronously at 192kHz) are sent to a remote server in a compressed lossless format, together with contextual information like tap position and temperatures.
A first set of algorithms is then run on the waveforms to extract RMS envelopes and aggregated statistics like Motor Current Index (MCI), current peak, and other standard Thermo-Electro-Mechanical (TEM) indexes.

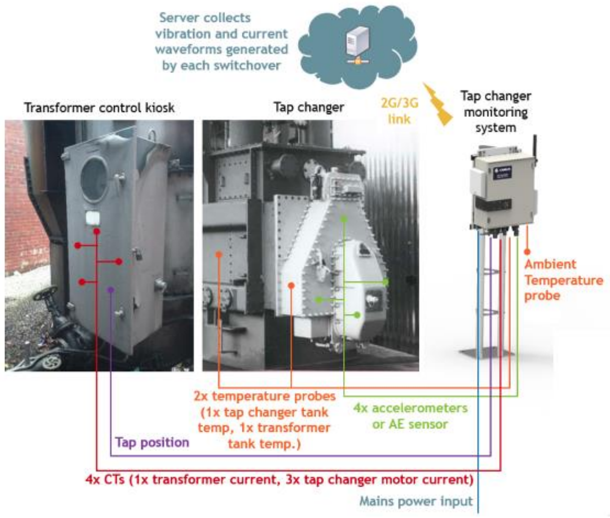

Fig.1 Monitoring system and sensor location

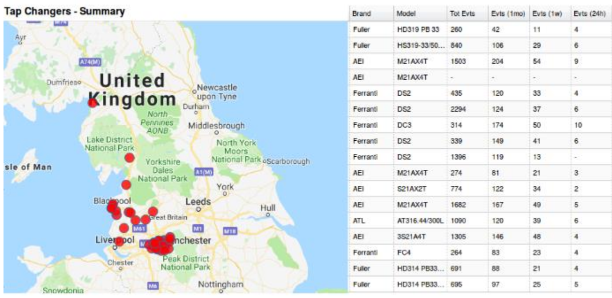

Fig.2 Web-tool showing monitored OLTC

Raw waveforms are also stored to allow for more advanced analysis and correlation to be carried out in next project phases. All the sites are reachable from remote by CAMLIN operators using an internal web-based tool (Fig. 2). For each tap changer it is possible to retrieve the historical data of the operations as well as the extracted parameters (Fig.3) and raw data.

ADAPTIVE THRESHOLD ON MOTOR CURRENT INDEX

Figure 4 shows the MCI trend over more than one year span. It can be seen that the parameter continuously varies over time. If plotted together with the tap changer oil temperature it is possible to notice an inverse dependency: the MCI parameter decreases with the increase of temperature and vice-versa. It is clear that choosing a fixed value for an alarm threshold on this parameter is not trivial due to the trend fluctuations.

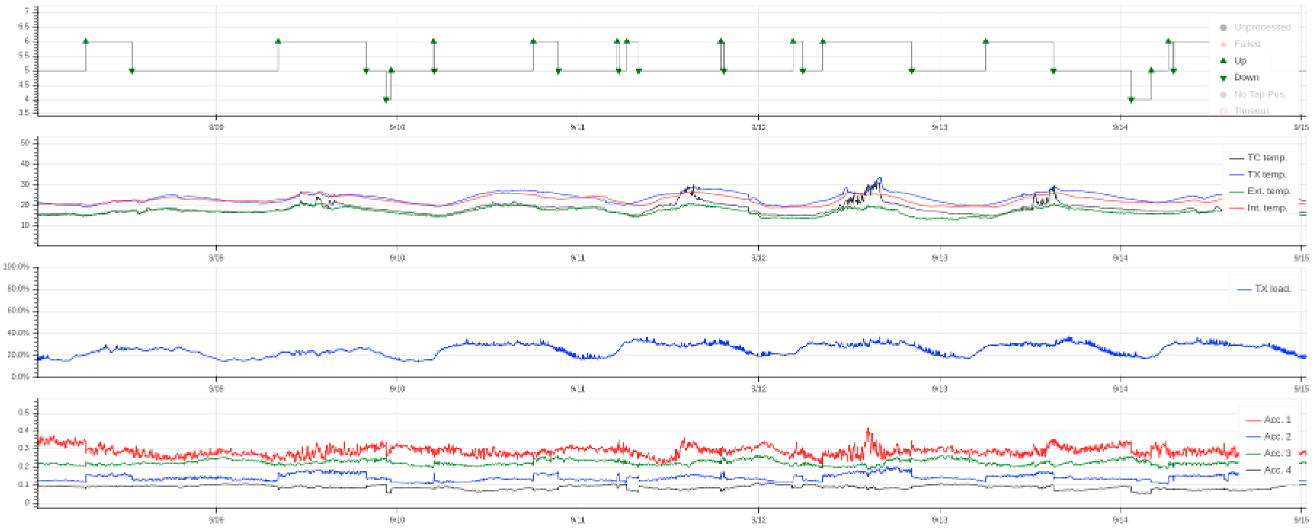

Fig.3 Web-tool showing parameter trends computed from raw data

Figure 5 summarizes the trends of Figure 4 in a simple scatter plot with MCI on Y-axis and OLTC temperature on X-axis. Each dot corresponds to a switchover event (UP or DOWN) and the colour takes into consideration the previous operation, thus creating four families which are: UP-UP, UP-DOWN, DOWN-DOWN, DOWN-UP.

The resulting map shows two well separated clusters with significantly different MCI. It seems that all the events of the type UP-UP and DOWN-DOWN have very similar MCI and significantly smaller than the MCI for the events UP-DOWN and DOWN-UP. From this simple analysis it is already possible to see that the user should set multiple thresholds in order to detect anomalies, depending on the type of event. In addition to that, the same type of operation shows a variability in the MCI due to the temperature dependency which further complicates the choice of a proper alarm threshold.

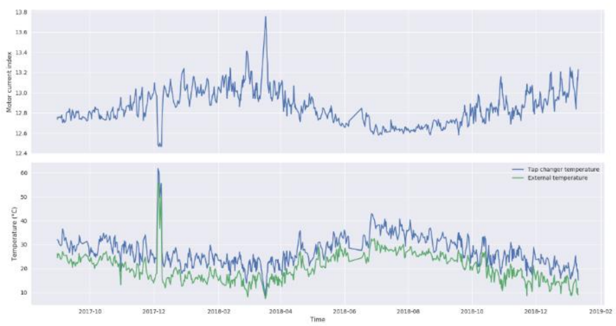

Fig.4 Trend data of MCI (bottom) for more than one year versus LTC temperature (top)

To overcome the manual thresholding problem, Machine Learning (ML) algorithms were used. The k-Nearest-Neighbours (k-NN) is a simple non-parametric machine learning algorithm used for regression and classification. Its robustness and interpretability are suitable qualities to perform regression and anomaly detection [5].

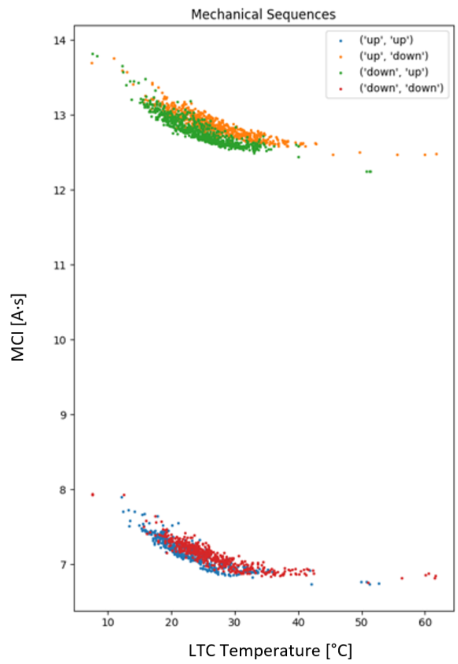

Fig.5 MCI index vs. temperature for the 4 different sequences

Historical observations of MCI and associated operating conditions (like transformer, tap changer and environmental temperature and transformer load) are used to train the algorithm. For every new event, the k-NN provides as query results the *k* most similar past observations from which we infer the expected MCI value and its confidence interval. In this way it is possible to observe anomalous values every time the actual MCI falls outside the predicted confidence band. By changing the number of *k*, it is possible to tune the sensitivity of the anomaly detector: higher values of *k* are likely to provide wider bands. By setting *k* to 5 and further widening the

obtained confidence band by 3% it was possible to minimize the number of false positives while maintaining high sensitivity to MCI variations and, thus, potentially detect developing faults.
A few results are shown in Figure 6 where the predicted (dark blue line) and real (orange line) MCI curves show very good fitting. The pale blue area around the trend represents the confidence interval: real MCI values falling outside this area could be labelled as “anomalies” and call for a deeper data review and analysis when not followed by on-site inspections.

Fig. 6 Actual (orange line) and predicted (blue line) MCI trends

As an exercise, the predictive algorithm was applied to all monitored tap changers not only for MCI but also including other standard TEM indexes like Motor Operation Time and Inrush Current.

Figure 7 shows a case where the actual measurements for MCI and Inrush Current suddenly started to deviate from predicted values, despite operating conditions where identical to the previous year in terms of transformer load and temperatures. A justification for this drop was found in the sudden decrease of the motor current (about 5%) independently from other conditioning factors. The real reasons behind this change are still under investigation but in principle it could be likely due to a reduction of motor supply voltage coming from a substation auxiliary transformer which in turn could be affected by a change in the distribution network configuration. As a matter of facts, the motor voltage was not measured by our monitoring system on this tap changer and it should be included in future systems to get a more comprehensive picture. Despite this being or not induced by a tap changer defect, this example shows:

- The potentiality for predictive algorithms to learn the normal behaviour and highlight anomalies (still to be analysed by experts and transformer operator)
- The need to increase the number of sensors as much as possible (for instance, adding the motor voltage among the inputs, the algorithm could have not highlighted any anomaly). The effectiveness of the algorithm in reducing false positive increases with the number of monitored parameters.
- The ineffectiveness of using simple thresholds on the MCI and other indexes due to their high variability in normal conditions.

Fig. 7 Actual data (orange line) deviates from predicted (blue line) MCI

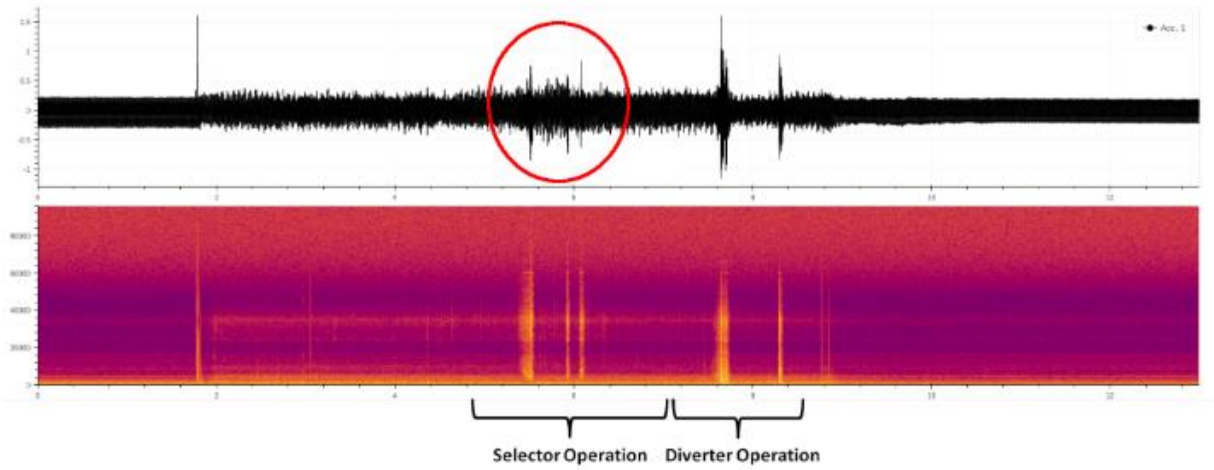

Fig. 8 Acoustic waveforms (top) and spectrogram (bottom) for a suspected operation showing arcing activity

ACOUSTIC ANALYSIS

Each tap changer was equipped with 4 high quality industrial Integrated Electronics Piezo-Electric (IEPE) accelerometers with resonance frequency of 40kHz and with good sensitivity up to 80kHz, thus suitable for both mechanical timing defect identification and electrical (arcing) detection.
Figure 8 shows the recorded waveforms and relative spectrogram during both selector and diverter operation of a DC3 Ferranti Tap Changer. It is possible to notice the presence of several acoustics events during the operation. While the diverter operation is impulsive and naturally results in emission of a strong mechanical noise, the selector operation should be quite noiseless. The sound event circled in red occurred during the selector operation has a frequency spectrum reaching up to 80kHz, thus being likely due to electrical arcing. It must be stressed that this happened only when selector contacts slid across the most used tap while under load. ENW eventually called for an outage to inspect the OLTC compartment.

CONCLUSIONS

The work presented is the first part of a pilot project carried out by ENW and CAMLIN Power aimed at collecting as many data as possible from 42 Tap Changers continuously monitored online. Several information including temperatures, transformer load, tap position, and waveforms about motor current and acoustic signals have been recorded and stored in a remotely hosted cloud-based server to allow a team of data scientists and transformer experts to analyse them.
As a result of this first part of the trial it looked clear that using a conventional method based on simple thresholds on parameters such as inrush current or motor current index has significant limits due to the huge variability of these parameters even in normal conditions. Indeed, the motor current index and operation time is, for some tap changer type, heavily dependent on temperature and on the previous operation (if it was a UP or DOWN). Advanced algorithms taken from the Machine Learning field, such as the k-NN, aimed at allowing a comparison between the real data with the predicted data seem to be more suitable to detect anomalies in an automated way.
In addition to that, there seems to be a substantial value in adding the readings from vibro-acoustic sensors which can provide more detailed indications on anomalous sounds of both mechanical and electrical nature. On this purpose, the next step of the project will consist on testing new ML algorithms including the acoustic waveforms as well as planning a field activity on all the tap changers where anomalies were detected to carry out offline DGA and Dynamic Resistance Measurement.

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