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OLTC Contact Monitoring using Vibro-Acoustic Signals and Time Series Forecasting

F. Dabaghi-Zarandi[1], P. Picher[2], M. Gauvin[2], H. Ezzaidi[1], I. Fofana[1], U. Mohan Rao[1] and V. Behjat[1]

[1]Research Chair on the Aging of Power Network Infrastructure (ViAHT),
University of Quebec at Chicoutimi, QC G7H 2B1, Canada
[2]Institut de recherche d'Hydro-Québec, Varennes, QC J3X 1S1, Canada

SUMMARY

On Load Tap Changer (OLTC) incipient faults detection is important to prevent power transformer outages and increase the system reliability. One of the most promising monitoring techniques is vibro-acoustic signal analysis. Over time, the OLTC contacts degrade due to factors including oxidation, coking, mechanical wear, and arcing. The contact degradation affects vibro-acoustic signals, therefore, tracking the changes in vibro-acoustic signals allows the condition monitoring engineers to assess OLTC condition.

Vibro-acoustic monitoring modules have been installed on transformers of the Hydro-Québec's network. The monitoring modules have recorded thousands of tap changes. Nevertheless, no evidence of contact degradation has been witnessed so far. For this reason, contact degradation has been simulated from the recorded signal envelopes using linear and non-linear amplitude increases.

This paper investigates time series forecasting models to prognose contact degradation. The presented methodology is envisaged as a prospective tool to allow the condition monitoring engineers to preventively plan the next OLTC contact replacement as part of a condition-based maintenance program.

KEYWORDS

Vibro-acoustic signals, OLTC contact, Power transformer, Time series forecasting

Fataneh.dabaghi-zarandi1@uqac.ca

1. INTRODUCTION

OLTC is one of the most important components in power transformers and its function is to regulate the voltage level by adding or subtracting turns to either the high voltage or the low voltage winding. Statistics show that around 27% of transformer failures and outages are due to OLTC failures [1]. There exists several techniques to detect OLTC faults such as dynamic resistance measurement, dissolved gas-in-oil analysis and vibro-acoustic signal analysis, and each of them can detect some OLTC faults [2]. In this paper, vibro-acoustic signal analysis is explored.

One of the key components in OLTC is electrical contacts. Over time, these contacts degrade gradually due to many factors including oxidation, coking, mechanical wear and arcing [3]. Contact degradation affects vibro-acoustic signals generated by tap changes. One of the challenges is to interpret these changes properly. In this research, the forecast of future vibro-acoustic envelopes, based on current and previous measurements, is studied. This prediction aims at determining the rate of contact degradation to make a prognosis and recommend a contact replacement when it is required to do so. A monitoring system installed on several transformers allows recording the following data for each tap change: vibro-acoustic signature, motor current, tap position and temperature [4]. The monitoring systems have recorded thousands of tap changes of transformers in service. Since no evidence of contact degradation has been observed, this paper investigates simulated vibration signal envelopes to represent contact degradation. Previous measurements before and after maintenance, using an instrument for periodic testing, allowed the understanding of the effects of various OLTC faults on vibro-acoustic signals, including contacts wear. Simulated degradation can be achieved with the modification of vibro-acoustic signals in a way that mimics this failure mode [5].

Time series forecasting is used to predict the future behavior of a system. This forecasting can be obtained based on the current and past conditions of the system. There are several forecasting models, such as AutoRegressive Integrated Moving Average (ARIMA), Long Short-Term Memory (LSTM), and Double Exponential Smoothing (DES), and that are used to forecast the future status of a system [6].

The remainder of this paper is structured as follows: section 2 explains the failure modes of OLTC contacts, section 3 represents data preparation, section 4 describes proposed algorithm, section 5 explains results and discussion, and section 6 concludes the article.

2. FAILURE MODES

There are several origins that cause degradation of OLTC contacts which are explained in the following [3, 7].

- **Oxidation:** Copper and silver are the most common materials used in OLTC contacts. The oxidation forms a film on the contact surfaces which leads to high contact resistance that affects OLTC operations [3, 7].
- **Coking:** Carbon is extracted from the surrounding oil and is deposited on contacts. This process appears when the contact is very hot because of the required energy. The carbon layer on the contact surface has two destructive effects: to increase the contact resistance and to lower the thermal conductivity [3, 7].
- **Pitting:** Pitting is a type of localized corrosion that creates small holes or cavities in the metal. Compared with uniform corrosion, pitting is more dangerous because the process of

detecting, predicting and designing against this type of corrosion is more difficult than uniform corrosion [7].

- **Mechanical Wear:** The loss of material due to mechanical action is considered mechanical wear [3]. In this regards, abrasive and adhesive wear are two fundamental types of mechanical wear related to OLTC contacts. In abrasive wear, one contact cuts into another which leads to creating a groove on the contact. In adhesive wear, any shearing or rupturing on the adhesive contacts can destroy the two contact surfaces [3, 7].

In addition, there are several other factors that can lead to accelerated contacts degradation. Some of these factors include high load current, low contact pressure and high temperature exposure [8, 9]. One example of contact degradation is displayed in Figure 1.

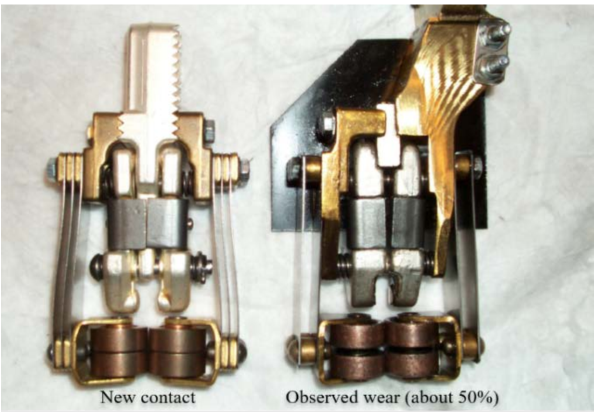

Figure 1: New contact and contact with observed wear of about 50%.

3. DATA PREPARATION

According to previous researches, OLTC operation with a worn contact generates a vibro-acoustic signal with higher amplitude [5]. A variation of the signal amplitude can then be done to simulate contact wear or degradation. A signal envelope measured on an OLTC in good condition is used as a reference. This reference signal is altered using a software that allows time and amplitude displacements. Many envelopes are generated using this process to simulate contact wear over time. Noise is added to the envelopes to simulate real life measurements.

In this paper, the behavior of contact degradation is simulated by increasing the amplitude of the envelopes linearly and non-linearly over 1,400 operations. Eight datasets are generated under different conditions. In dataset D1, the envelopes are generated with a linear increase without adding any noise. In dataset D1N1, white noise N1 is added to D1. In dataset D1N2, the amount of noise is increased to level N2, and in dataset D1N3, the noise is increased again to level N3. In the fifth to eighth condition, the envelopes are generated like the first four, but this time the amplitude is increased non-linearly (D2, D2N1, D2N2 and D2N3).

Figure 2 shows simulated envelopes with linear and nonlinear increases, without any noise. To display the pattern of upward trend, the same number of operations (200) is kept between shown envelopes. For better observation, graphs (b) and (d) display a zoomed view of graphs (a) and (c). Envelope 1 was measured from a real OLTC operation with contacts in good condition, and the other envelopes are simulated.

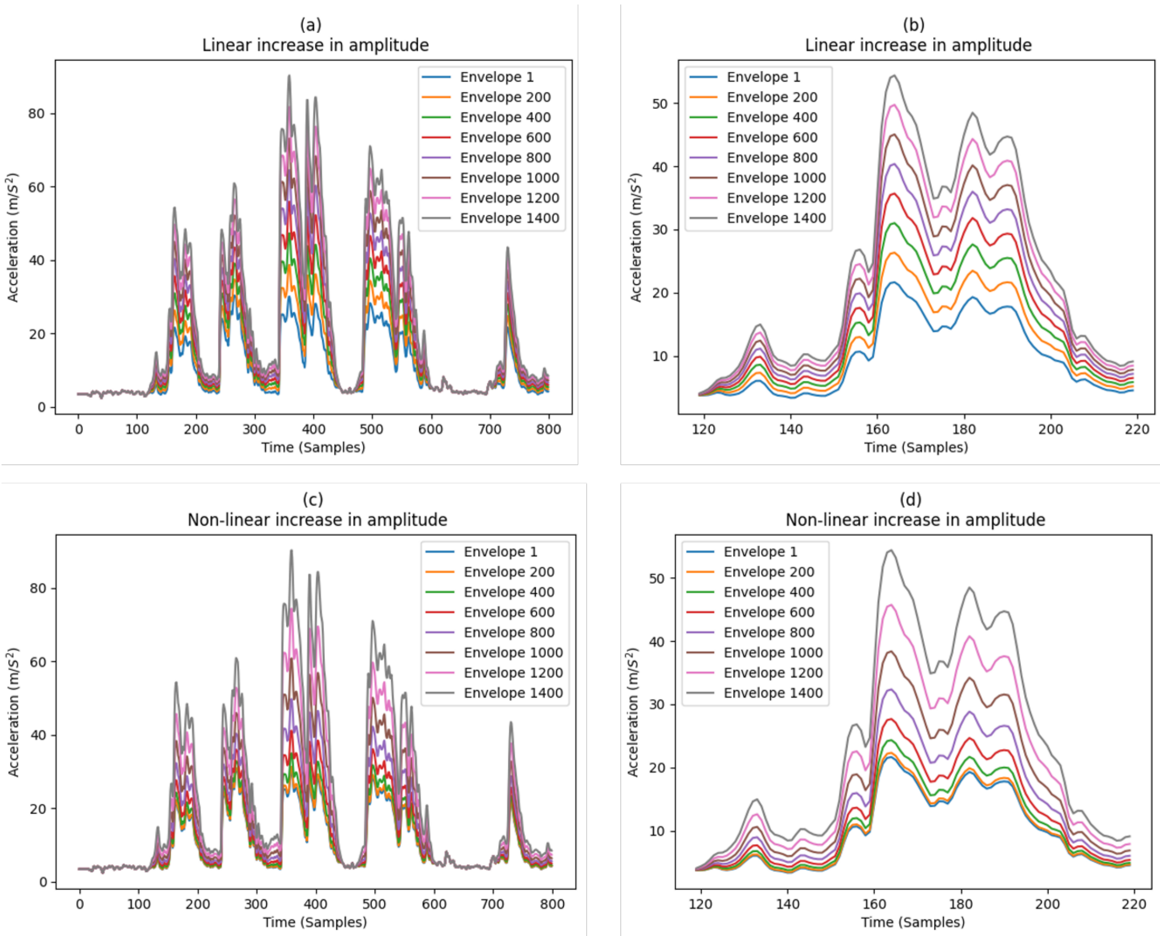

Figure 2: Simulating envelopes related to contact degradation.

4. PROPOSED ALGORITHM

To predict envelopes, the time series forecasting models ARIMA, LSTM, and DES are investigated [10, 11]. The datasets are subdivided in two groups: around 70% of the data (1,000 envelopes) for training and the remaining (400 envelopes) for test. The performance of the trained models are assessed using Root Mean Square Error (RMSE) [6].

The following algorithm is implemented:

a. The data values of the envelopes are put in a matrix (800 samples x 1,400 envelopes)
b. Each forecasting model is trained with 1,000 envelopes, and then tested using the remaining 400 envelopes
c. For each envelope sample, the forecasting model with the lowest RMSE is recorded and this forms a combined model
d. The combined model is tested with the same 400 envelopes as in step b.

5. RESULTS AND DISCUSSION

Prediction results from simulated signal envelopes without adding noise (D1 and D2)

The forecasting results obtained in the datasets D1 and D2 are displayed in Figure 3 and Figure 4. As shown in the figures, the pattern of upward trend in the prediction envelopes is like the training set. The numerical RMSE values are reported in Table 1.

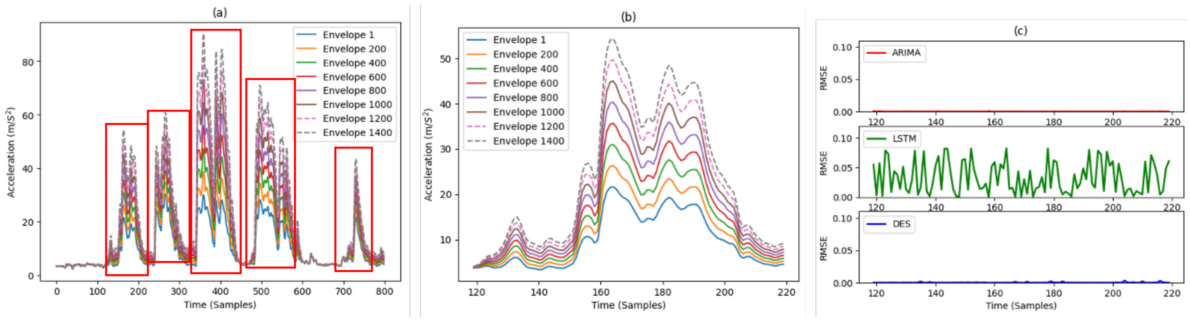

Figure 3: (a), (b) The training and predicted envelopes (dashed lines) by combined model applied on D1 dataset and (c) RMSE data used to select the best forecasting model for each sample of graph (b)

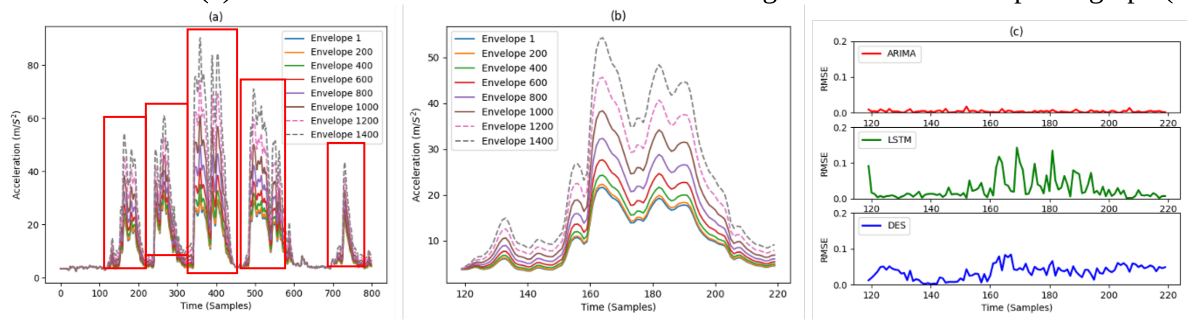

Figure 4: (a), (b) The training and predicted envelopes (dashed lines) by combined model applied on D2 dataset and (c) RMSE data used to select the best forecasting model for each sample of graph (b)

Prediction results from simulated signal envelopes with added noise (D1 and D2 + N1, N2, N3)

The prediction results from simulated signal envelopes D1 and D2 with noise levels N1, N2 and N3 are displayed in Figure 5 and Figure 6. The numerical RMSE data are reported in Table 1.

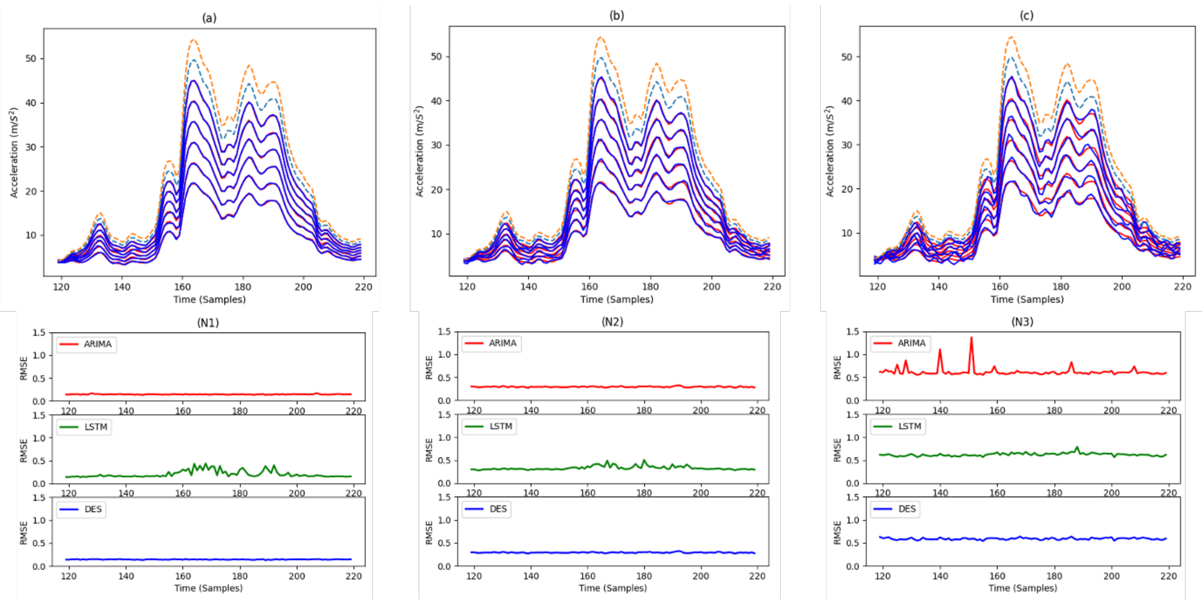

Figure 5: The training and predicted envelopes (dashed lines) by combined model applied on D1 dataset with (a) N1, (b) N2, and (c) N3 noise level. Simulated envelopes without noise are in red and simulated envelopes with noise are in blue. RMSE data used to select the best forecasting model for each sample are shown below the graphs.

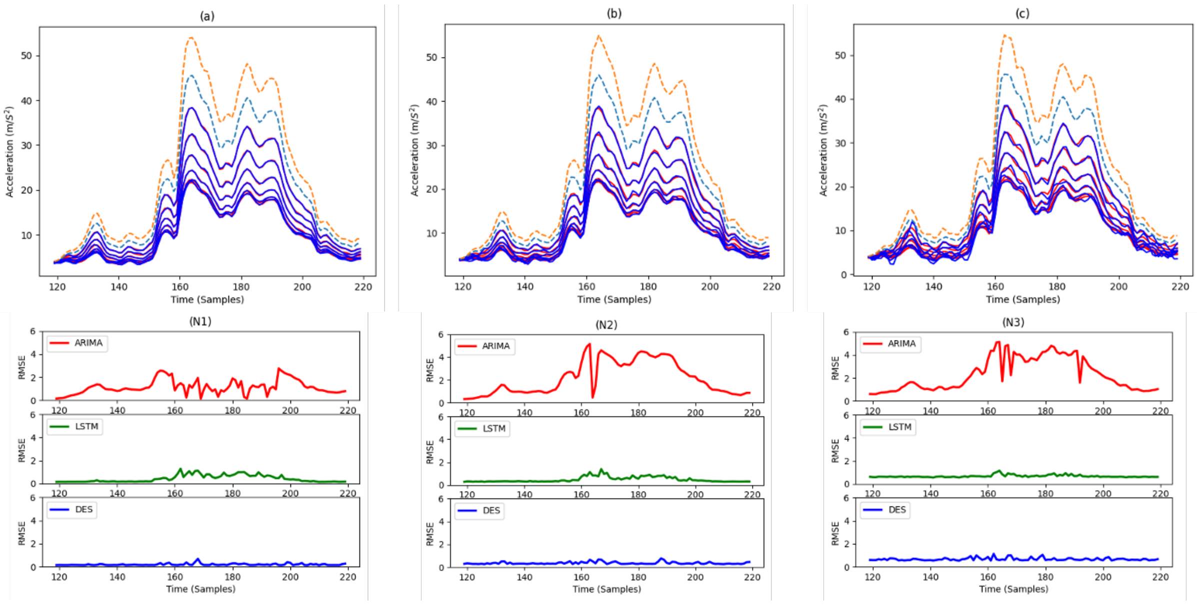

Figure 6: The training and predicted envelopes (dashed lines) by combined model applied on D2 dataset with (a) N1, (b) N2, and (c) N3 noise level. Simulated envelopes without noise are in red and simulated envelopes with noise are in blue. RMSE data used to select the best forecasting model for each sample are shown below the graphs.

Table 1 summarizes all the results. The following remarks can be made:

- RMSE obtained from datasets D1 and D2 are close to zero which indicates the high accuracy of the proposed algorithm
- Noise causes a decrease in the accuracy of the prediction models (increased RMSE)
- As expected, the combined mode is more effective than any model taken separately
- ARIMA's performance is significantly decreased when tested with D2N1, D2N2 and D2N3 datasets, as also observed in [12].

Table 1: Numerical RMSE values for different prediction models, average for samples 119 to 219

#	Dataset	Description	Average RMSE Combined model	Average RMSE ARIMA/LSTM/DES
1	D1	Linear increase without noise	0.000295	0.000324/0.033172/0.000562
2	D1N1	D1 + noise level N1	0.144955	0.146147/0.204034/0.145089
3	D1N2	D1 + noise level N2	0.291753	0.292936/0.32787/0.292101
4	D1N3	D1 + noise level N3	0.590716	0.617336/0.619979/0.591528
5	D2	Non-linear increase without noise	0.00338	0.003968/0.027673/0.036067
6	D2N1	D2 + noise level N1	0.190707	1.144173/0.424071/0.203751
7	D2N2	D2 + noise level N2	0.344645	2.165089/0.476722/0.363704
8	D2N3	D2 + noise level N3	0.624953	2.291216/0.669303/0.672139

6. CONCLUSION

In this paper, time-series forecasting models are investigated as a prospective tool for analyzing vibro-acoustic signals for OLTC contact monitoring. The idea is to develop an algorithm that could prognose the health of the contacts, to preventively plan their replacements as part of a condition-based maintenance program.

Simulation of contact wear is performed with linear and nonlinear increases of the amplitude of a real vibro-acoustic envelope measured on a transformer in service. Noise is added to represent real measurements in a high-voltage substation. A total of eight datasets containing 1,400 envelopes each are used to investigate three time-forecasting models.

The results show that the proposed algorithm can prognose adequately a contact wear translated by a linear or nonlinear amplitude increase of the vibro-acoustic signal. The proposed methodology, investigated with simulated signals, shows an interesting potential for future applications and developments of prognostic techniques applied to vibro-acoustic monitoring data.

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