Condition Assessment of AC Contactors Using Optical Fiber Sensors and Deep Learning

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***Abstract*—Electromechanical contactors are core equipment of the electrical circuits environment, operating mainly in industrial areas for load control. As they have a lifespan and are susceptible to faults, predictive maintenance based on measurement systems is crucial to avoid accidents and profit loss. This paper presents a method of instrumentation and analysis of AC contactors under different operational conditions. Optical Fiber Bragg Grating (FBG) sensors were used as sensor elements. The experimental setup relied on two ABB AX40 AC contactors, each instrumented using a single FBG sensor externally. The devices were subjected to three switching conditions: the contactor with no faults, worn load contact, and end-life load contact. The events were submitted to different variability conditions to better generalize the system for field application. Continuous Wavelet Transform (CWT) generated scalograms from the acquired signals to be submitted to different Convolution Neural Networks (CNNs) models. The data set was split between the training, CNN validation, and repeatability test groups. This third group is a set of conditions not trained with the classifier to verify the generalization. The results presented in this paper show a high F1 score of around 0.9 for the CNN architectures in the training group and validation groups. However the repeatability test group had lower results, being around 0.3. This paper shows the high applicability of FBG as single sensor element and CNN to monitoring and classifying faults in electrical switching devices, with further studies aiming for field application.**

***Index Terms*—Fiber Bragg Gratings, Switching Devices, Deep Learning**

I. Introduction

Electromechanical contactors are used in electrical systems mainly in industrial areas for load control, becoming a fundamental part of electrical circuits, however they are susceptible to malfunctions. Some of these faults are the carbon's deposit obstructing the inner contact [1], core or contact blockage, voltage sag and contact bounce [2]. Switching devices such as On Load Tap Changers (OLTC) transformers and circuit breakers are already monitored by measurement systems [3], [4]. They are based on sensors, normally non-invasive, that make use of mechanical vibration detection of switching conditions [5]. However the electrical sensors, such as accelerometers, are susceptible to external electromagnetic noise in field applications [6]. On the other hand, optical sensors such as Fiber Bragg Grating (FBG) are immune to electromagnetic influence [7]. FBG sensors have already proven its effectiveness in several switching devices researches using only a single sensor [2], [8], [9]. Although they have not yet been applied in a robust system with repeatability.

This paper proposes a real-time health monitoring system for an AC contactor, using FBG as the sensor and CNN for switching pattern recognition. The CNN is based on CWT-generated images from three data classes: no operation faults, load contacts wear-off, and end-life contacts. This work advances previous research on low power relays [8], [9], offering greater robustness and flexibility in fault analysis. Moreover, the system's use of CNN and focus on repeatability enhance its field reliability.

II. Materials and Methods

A. Experimental Setup

The tests were carried out using two AC contactors of the same model ABB AX40. This device works based on electromechanical force generated a coil connected to an AC source of 220 V AC, which attract the movable part of the ferromagnetic core to its fixed one. This action also close the load contacts, allowing electrical current to pass. When the source is off, a return spring brings the moveable core and the load contacts back to their original position [10].

The arrangement relied on FBG sensors and an interrogator I-MON 256, with 4k Hz of acquisition rate and 20 μs of exposure time to acquire the sensors signals. The FBGs were fixed to the contactors cases with a cyanoacrylate-based glue to acquire the mechanical vibration, as presented in Figure 1.

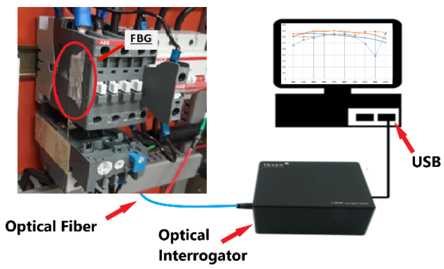

Fig. 1. Representation of the experimental setup for measurements.

The FBG is defined as a periodic modulation of the optical fiber core refractive index, that reflects part of the incident light spectrum, which is called Bragg wavelength. This reflection is susceptible to mechanical deformations and temperature changes [11], [12]. We used four FBG sensors separately for each test round, three for one contactor and the last one for the other. The optical fiber used was the GF1 Thorlabs type. Regarding the FBGs parameters, all of them had different Bragg wavelengths and the reflectivity above 80%. This procedure aimed to achieve the best adaptability for different FBGs.

The experiment consisted of capturing the mechanical signal of the closing contacts, keeping it connected for 3 seconds to avoid any trace of mechanical waves from the first event, and opening the contacts again, also taking this vibration. It is noted that the temperature does not undergo large amplitude changes in this arrangement and time window. This implies that temperature does not significantly influence the Bragg wavelength variation with the small time window of the acquired signal.

In addition to the acquisition system, the contactor was operated under three load conditions. Non-load switching, an inductive motor with 15 horsepower switching and three-phase heating resistance switching. Regarding the resistances, they were connected in triangle and placed in a water reservoir, dissipating 5.4k W each.

B. Data set

The carried out test procedure acquired 3 classes of data, 435 samples of the contactor at healthy state (Class 1), 210 with load contact wear-off (Class 2) and 210 with end-life load contact (Class 3). All these samples were divided between the contactor (C1 or C2), the sensor (S1, S2, S3 or S4) and the load condition of the contactor (no-load (NL), resistance (R) or motor (M)). The variability imposed by changing between FBGs, contactors and different tpes of loads provides better generalization and repeatibility for the CNN classifier. The data set is thorougly detailed in Table I showing the classes, sensors, contactors and its respective samples number. The classes are visually displayed by colors.

TABLE I
DATA SET SHOWING THE NUMBER OF SAMPLES FOR EACH CLASS AND VARIABILITY.

	S1 C1	S2 C1	S3 C2	S4 C1
CLASS 1 NL	40	40	40	25
CLASS 1 R	40	40	40	25
CLASS 1 M	40	40	40	25
CLASS 2 NL	15	15	15	25
CLASS 2 R	15	15	15	25
CLASS 2 M	15	15	15	25
CLASS 3 NL	15	15	15	25
CLASS 3 R	15	15	15	25
CLASS 3 M	15	15	15	25

The data set was split between training, validation and test groups. The first two were composed by S1C1, S2C1 and S3C2, this data was randomly split in 66.6% for training and 33.3% for validation. As for the test group, it only used the S4C1 data to evaluate the predictive quality of the classifier and the repeatability of the system for field application.

C. Algorithm

All signals were submitted to a pre-treatment procedure. The data was normalized, denoised and the opening and closing events of the contactor were extracted from the main signal in a time window of 1.024 seconds with each event centralized. These two separate signals form a contactor data sample.

The closing and opening events were submitted to CWT, generating two main images. The center of the images (0.45 to 0.55 seconds) was extracted as the main signal (1, 4). Two additional images were acquired from each event, those being the zoom on the window frequency of 0 to 500 Hz (2, 5) and 1000 to 1500 Hz (3, 6), since it has important power spectral density components. All of the six generated images were merged into a single one to use at the classification algorithm as shown in Figure 2, where red colors represents denser frequencies than blue colors.

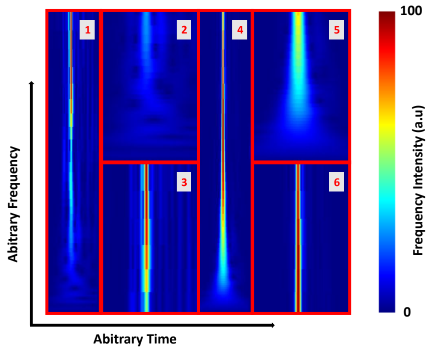

Fig. 2. Example of the processed data of the contactor 1 at healthy state with no load and sensor 1.

For this experiment, three types of convolutional neural networks architectures were used, with the weights established and stored in the Keras library. MobileNetV2 is a network proved to be useful in radar's scalogram classification [13], EfficientNetB3 has a great performance in electroencephalogram's scalogram classification [14] and ResNet50 was also used to compare with the other two.

III. Results and Discussion

To choose the ideal CNN, the three architectures were submitted to the training and validation data sets. For all of them, the layers of the transfer learning were frozen and two additional dense layers of 2042 neurons with 20% of dropout were implemented. The size of the input images consisted of a square of 512 x 512 pixels for the MobileNetV2 and ResNet50 and 256 x 256 for the EfficientNetB3, due to implications in the architecture.

Since the data is unbalanced, F1 macro was chosen as the evaluation metric. This metric is a harmonic mean of false positives and false negatives, being better than accuracy for this data set. It has a range value from 0 to 1, with its better result being 1. The loss function of the algorithm is also implemented. This function updates the weights of the CNN based on the outcome, lesser values indicate better performance. The final results of the F1 metric and the loss function of the CNNs using 12 epochs is presented in Table II.

TABLE II
LOSS AND F1 VALUES FOR EACH TRAINED CNN

Function/CNN	MobileNetV2	ResNet50	EfficientNetB3
Train loss	**0.20**	0.30	0.20
Train F1	**0.94**	0.90	0.94
Validation loss	**0.31**	0.42	0.37
Validation F1	**0.91**	0.82	0.89

By Table II, it is possible to imply that MobileNetV2 achieved better results based on the lesser value of the loss function and the higher results of the F1 metric. It is important to indicate that the three architectures had their saturation in 12 epochs and MobileNetV2 is less computationally expensive than other CNNs such ResNet50.

Despite the F1 presented in the training and validation data sets being close to 90%, the repeatability tests had questionable accuracy values. Accuracy is used for balanced data, like the test group. The final results of the accuracy for the test group varied between 0.21 and 0.30 with best result being EfficientNetB3.

The low repeatability for the proposed monitoring system could indicate an improper installation of the sensor from the test group, however if we rearrange the data set so that the other sensors are in the test group, the problem persists for each FBG. This leads to the understanding that the problem may be in the small physical variations of the installation, making so an undetectable overfit of the CNN occurs based on the input information. To solve this problem, data augmentation, sensor encapsulation and feature selection can be implemented.

All FBGs sensors were able to identify classes in the training and validation group, even with slightly different parameters. It was possible to acquire the contactor vibration signals up to 2 kHz with only a single FBG sensor element and submit them to a neural network for fault detection with high F1 metric score. Although additional criteria must be taken to ensure repeatability, the system has potential for application.

IV. CONCLUSION

The results obtained in this work show that for the classification of different defects in contactors is feasible using features extracted from scalogram images, provided by just a single FBG sensor, and convolutional neural networks. On the other hand, it is not possible to generalize the classification of a new data set to a pre-trained model where there is not a significant number of measurements in different conditions within the base model. This behavior should be confirmed in future studies, suggesting other control measures to guarantee the repeatability of the experiments, although some, such as calibration of the optical source gain and locking of the contactor base, have already been carried out. Other works we have in progress are to encapsulate the FBG for fixing the same sensor on different contactors. If this verification still produce the results obtained in this work, this may indicate that due to the size of the internal components, the failure conditions in contacts are very close to the normal operating state.

Given this, another promising work in progress is to analyze the features extracted in frequency and time. Attributes based on Power Spectrum Denstiy can be used for detailed analysis to select outstanding features and discard others. Furthermore the database raised in this work can help study statistical deviations that can be correlated to some defects.

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REFERENCES

[1] W. Rieder and T. W. Strof, "Reliability of commercial relays during life tests at low electrical contact load," *IEEE Transactions on Components, Hybrids, and Manufacturing Technology*, vol. 15, no. 2, pp. 166–171, 1992.

[2] C. C. Tapia, J. L. R. Ortiz, U. J. Dreyer, J. C. C. da Silva, and K. de Morais Sousa, "Evaluation electromagnetic contactor magnetic core temperature and dynamic strain using fiber Bragg gratings," *Measurement*, vol. 166, p. 108174, 2020.

[3] A. I. Khalyasmaa, M. D. Senyuk, and S. A. Eroshenko, "High-voltage circuit breakers technical state patterns recognition based on machine learning methods," *IEEE Transactions on Power Delivery*, vol. 34, no. 4, pp. 1747–1756, 2019.

[4] A. Cichoń, T. Boczar, P. Fracz, and D. Zmarzły, "Detection of defects in on-load tap-changers using acoustic emission method," in *Proc. International Symposium on Electrical Insulation*. IEEE, 2012, pp. 184–188.

[5] J. Seo, H. Ma, and T. K. Saha, "Analysis of vibration signal for power transformer on-load tap changer (OLTC) condition monitoring," in *Proc. Power & Energy Society General Meeting*. IEEE, 2018, pp. 1–5.

[6] H. Hoidalen, M. Runde, O. Haugland, G. Ottesen, and M. Ohlen, "Continuous monitoring of circuit-breakers using vibration analysis," in *Proc.* 11^{th} *International Symposium on High Voltage Engineering*, vol. 1. IET, 1999, pp. 102–106.

[7] A. Mohammed, J. I. Melecio, and S. Djurović, "Stator winding fault thermal signature monitoring and analysis by *in situ* FBG sensors," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 10, pp. 8082–8092, 2018.

[8] D. Benetti, E. H. Dureck, U. J. Dreyer, A. E. Lazzaretti, D. R. Pipa, and J. C. C. da Silva, "Classification dynamic strain patterns in switching devices measured with fiber Bragg grating," in *Proc. of SBMO/IEEE MTT-S International Microwave and Optoelectronics Conference*. IEEE, 2021, pp. 1–3.

[9] E. H. Dureck, D. Benetti, U. J. Dreyer, and J. C. C. da Silva, "Fault analysis in electromechanical relays's switching using fiber Bragg grating," in *Proc. of SBMO/IEEE MTT-S International Microwave and Optoelectronics Conference*. IEEE, 2021, pp. 1–3.

[10] J.-R. R. Ruiz, A. G. Espinosa, and L. Romeral, "A computer model for teaching the dynamic behavior of ac contactors," *IEEE Transactions on Education*, vol. 53, no. 2, pp. 248–256, 2009.

[11] A. Othonos and K. Kalli, *Fiber Bragg Gratings Fundamentals and Applications in Telecommunication and Sensing*. Artech House Publishers, 1999.

[12] R. Kashyap, *Fiber Bragg gratings*. Academic Press, 1999.

[13] A. Hanif and M. Muaz, "Deep learning based radar target classification using micro-doppler features," in *2021 Seventh International Conference on Aerospace Science and Engineering (ICASE)*. IEEE, 2021, pp. 1–6.

[14] G. Maragatham, T. K. Devi, P. Savaridassan, and S. Garg, "Epileptic seizures prediction using deep learning methods on eeg recordings." *Webology*, vol. 17, no. 2, 2020.