14th IMEKO TC10 Workshop Technical Diagnostics
New Perspectives in Measurements, Tools and Techniques
for system's reliability, maintainability and safety
Milan, Italy, June 27-28, 2016

A diagnostic tool for Condition-Based Maintenance of circuit breaker

V. Pesenti Campagnoni[1], S. Ierace[2], F. Floreani[3]

[1] *Consorzio Intellimech, via Stezzano 87 - 24126 - Bergamo - Italy, valerio.pesenti@intellimech.it*
[2] *Consorzio Intellimech, via Stezzano 87 - 24126 - Bergamo - Italy, stefano.ierace@intellimech.it*
[3] *Consorzio Intellimech, via Stezzano 87 - 24126 - Bergamo - Italy, fabio.floreani@intellimech.it*

***Abstract* – Nowadays competitiveness of global market pushes managers to optimize all systems involved in their organizations in order to increase global efficiency and to improve Key Performance Indicators. In maintenance context this means reduce costs by optimizing interventions and eliminating unscheduled downtimes and breakdowns. To this end maintenance strategies have evolved from standard cyclic maintenance to more advanced approaches like Condition-Based Maintenance and Predictive Maintenance approach. Even if lot of work has been done regarding these methodologies applied on machines or industrial plants, the same care is not applied to other critical devices, such as Low Voltage Circuit Breakers, for which conservative approaches are generally applied. That implies a scheduled replacement of devices could occur with a significant Remaining Useful-Life. This paper deals with application of Condition-Based Maintenance approach to an electrical circuit breaker. The goal is to develop a diagnostic tool for Fault Detection, using 3-Sigma rule and Control Charts.**

I. INTRODUCTION

Nowadays competitiveness of global market pushes companies to optimize all systems involved in their organizations in order to improve Key Performance Indicators (KPIs) [1]. Consequently the concepts of quality, safety and reliability are becoming increasingly important [2]. In this sense an effective maintenance program can increase global efficiency since it aims to optimize interventions and to prevent unscheduled downtimes and breakdowns [3]. Most companies still need to undertake a breakthrough in carrying out their maintenance activities by shifting from a traditional "Fail and Fix (FAF)" approach to a "Predict and Prevent (PAP)" maintenance methodology [4]: the first one is a run-to-failure approach, which expects maintenance intervention only when a malfunction occurs, instead the second one is a time-based preventive maintenance, which plans intervention after a specified time period regardless the health status of a physical asset [5]. This strategy generally is not the optimal solution in terms of effectiveness and efficiency. In fact on one hand it is possible that maintenance intervention occurs long time before system health requires it. On the other hand, it is possible that fault occurs in the interval between two consecutive interventions, with elevated safety risks and significant costs. Recently, other maintenance approaches such as Condition-Based Maintenance (CBM) have emerged to support companies on this challenging area [6]. This maintenance policy requires corrective intervention only when the presence of anomalous behavior of the physical system, compared with normal operation, is detected by condition monitoring. It refers to diagnostic that aims to automate the processes of detection, isolation and identification of faults when they occur by monitoring the weak signals, characterizing health conditions of Physical asset [7]. The advantage of this strategy lies in the possibility of preventively maintaining the system only when necessary, saving resources and increasing system availability [8]. The natural evolution of CBM is prognostic that attempts to predict faults or failures before they occur and projects the Remaining Useful-Life (RUL) [9] of physical system through the use of automated methods.

CBM application results particularly advantageous for those industrial critical devices, located in harsh and difficult to reach environments, whose failures are extremely critical for safety. In this sense diagnostic/prognostic assessment is very important for circuit breaker, switches and contactors. The challenge for these kind of devices, characterized by a bistable behavior, is to maximize the information content provided by the equipment during the transient from one state to the other. This transient is typically really fast and not periodic in time. The frequency of use can range widely, from many maneuvers per day (in high-demand application) to one maneuver or less per year (in low-demand application). According to their usage many different factors could lead to undesired functioning. In order to select the best set of methodologies, sensors and acquisition systems, it is necessary to identify which kind of quantities are most suitable to indicate the health-state of the equipment. Aiming at this purpose, the first part of this work deals with the selection of a suitable set of sensors and their related signals, able to extract the highest possible number of information for diagnostic purpose about a Low Voltage Circuit Breaker (LVCB). In the second part an analysis of a wide set of methodologies will be conducted, in order to evaluate which algorithms are most suitable to evaluate Circuit Breaker (CB) health status. Finally an appropriate SPC tool will be described; this paper describes a first but important step for creating an efficient CBM for industrial CBs.

II. SIGNAL SELECTION

Proper selection of monitoring signals is the core of any effective diagnostic system, since all information regarding the health status of the system is contained in them. Consequently it is crucial to identify which signals can be significant to represent the status of the equipment, in order to monitor them, with an appropriate sensorization, and to have a correct visibility about the health status of the equipment. In literature, several papers deal with the selection of the more relevant signals and the related sensorization for High Voltage Circuit Breakers (HVCBs), while for LVCBs there are no significant studies. However despite many differences between these devices, some common points at functional blocks and features level are comparable, therefore it is possible to hypothesize that the indications found for HVCB can be used also in this specific case. Literature analysis reveals the most common HVCBs failure causes: in particular, the second CIGRÉ inquiry [10] on HVCBs reported that 44% of major failures and 39% of minor failures are of mechanical origin. Other relevant failures are of electrical nature, in particular related to control and auxiliary systems (25% of major failures and 10% of minor failures). Accordingly the monitoring system has to measure the quantities able to return information about the wear state of mechanic and electric components present in the CB. The most relevant mechanical monitoring technique is the vibration analysis of the equipment through accelerometers connected to specific parts of the CB. Vibration signals, generated by moving parts and shock during the operating maneuvers, in fact, can contain important information about the health status of the device; in this case diagnostic test consists in a comparison between a vibration, recorded during an opening/closing operation, and a reference accelerometric signature: any deviation between these two signals could mean a deviated health condition in the CB. Also the measurement of main contacts position during opening/closing operations is a useful tool to detect the presence of mechanical damage [11]: differences in the travel speed or in the movement amplitude in fact could be symptomatic of malfunctions. On the electrical side, several articles deal with the application of the Electrical Signature Analysis (ESA) [12] to the command parts of the CB; in particular electromechanical actuators that activate the opening/closing mechanism [13]. ESA is based on the comparison between electrical absorption signal with a reference one, in order to detect possible misalignments attributable to an electrical malfunction. This technique is generally coupled with other classical measurements, like the logical state of the contacts (open/close) [14].

Starting from the above considerations, an experimental test bench, reported in Fig.1, has been developed in order to obtain an experimental evaluation. A LVCB has been sensorized in order to measure: vibrations, caused by the collisions of main contacts and other mechanical parts during closing/opening maneuvers, current absorption of every control electromechanical part, angular position of the CB main shaft. Therefore, the related set of sensors used in the test bench is:

- A *capacitive tri-axial accelerometer*, belonging to MEMS technology [15], used to measure vibrations. This has been positioned on the CB main rod and oriented according to the three reference main axes.
- *Current Sensors*, one for each electromechanical device, used to obtain current absorption.
- An *absolute angular encoder*, linked by an elastic coupling, used to acquire angular position of the main shaft of the CB.

The main technical specifications of selected sensors are reported in Table 1.

Table 1. Main technical specifications

Parameter	Value
Tri-axial accelerometer	
Frequency range	0 – 12000 Hz (< 3 dB)
Sensitivity	2.2 mV/g
Nominal maximum acceleration (peak)	500 g
Maximum shock level (± peak)	4000 g
Operating temperature range	-40°C – +125°C
Current transducers	
Measuring principle	Hall Effect
Current range	±30 A
Output voltage range	±4 V (@ I = ±10 A)
Frequency range	0 – 50 kHz
Accuracy	±1 %
Encoder	
Number of turns	1
Resolution	16 bit
Measuring principle	Magneto-resistive
Output signal	4 – 20 mA
Maximum speed of rotation	6000 min^(-1)
Shock protection	2000 m⁄s^2

All signals have been acquired through an acquisition system composed by a NI PXI system equipped with the NI PXI-6123 board. In order to synchronize all the different elements of the acquisition system, a properly designed trigger generation board has been used; this board generates a square wave with three level of voltage, every level coincides with the activation of one of three specific phase (closing, charging, opening). Finally a PLC based sequencer has been properly programmed, in order to automatically perform a huge number of maneuvers simulating the overall CB life.

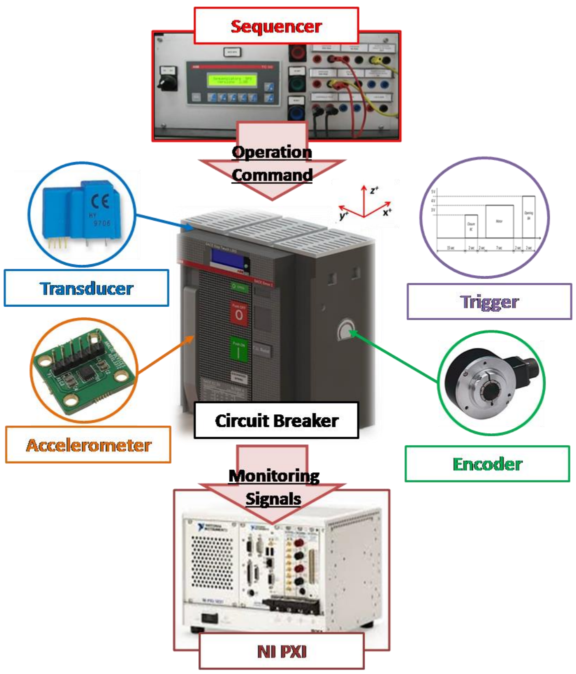

Fig. 1. Experimental test bench

III. FEATURE EXTRACTION

A common starting point to make diagnostic and prognostic, is the feature extraction. It consists in the generation, starting from experimental data, of significant features; these features synthesize information content of signals, in order to allow a better understanding of data and to facilitate the knowledge extraction. As a first step, a literature analysis has been carried out in order to identify different suitable solutions. Some author propose to find a set of considerable points of the measured time signal, i.e. those ones attributable to critical aspects or characteristics of the tested device (e.g. duration, amplitude, etc.). More accurate methods consider also the frequency domain; the basic one is the Fourier transform, usually used in its FFT version [16]. A variation is the Short Time Fourier Transform (STFT), that gives back the spectrogram of the time signal [17]. A more refined tool for increasing temporal and frequency resolution both is the Continuous Wavelet Transform (CWT) [18]. A completely different solution is the Empirical Mode Decomposition (EMD), that is an auto-adaptive decomposition algorithm [19]. Dynamic Time Warping (DTW), commonly used for voice recognition, is also used in several other applications, such as diagnostic techniques for industrial processes [20]. Hotelling T^2 [21] uses T^2 statistic to provide a solution to a multivariate detection problem. Other methods use energy or signal entropy as a basic quantity to define a feature: i.e. energy entropy of the Hilbert spectrum, Approximate Entropy and Sampled Entropy [22].

In order to evaluate the goodness and applicability of the afore mentioned indices in this study, a preliminary measurement session and a starting test activity has been performed. During this test phase various combinations of algorithms have been applied on real signals acquired from the CB. Due to the lack of any corrupted signal by an incipient failure, at the beginning, raw signals have been artificially manipulated in order to simulate trend variations from the nominal condition. Results coming from this phase gave back outline informations about algorithms sensibility in a real case.

For accelerations, that are impulsive signals with some high peaks and a fast decay, DTW has been chosen and evaluated. Given two vectors representing two time series, reference and test, DTW calculates, for every value of the test series, the best matching which minimize the temporal misalignment of the two series. The result of the algorithm is a distance value that is an index of similarity between two signals. In this specific case study the algorithm has been applied on power spectral density vectors (Fig. 2). Since DTW computational speed depends on the number of points, some tests have been conducted to determine the methodology which provides the best trade-off between algorithm performance and computational speed. The results have proved that best trade-off is obtained dividing spectrogram in a certain number of slices, respect to the time axis and frequency axis, and comparing every slice with the same one of the reference acceleration signal. This process gives back the DTW distances vector from which mean value is calculated.

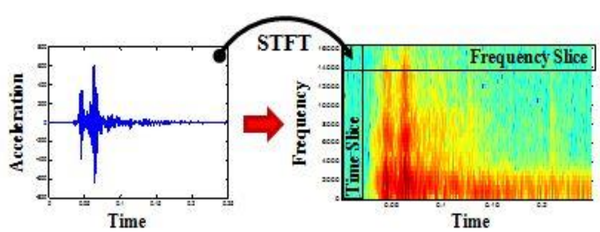

Fig. 2. DTW implementation

For current absorption Root Mean Square (RMS) of Current value at regime and time duration has been extracted, while angular position has been elaborated in order to extract the amplitude of the main shaft rotation in opening/closing operations and the relative time duration. Fig. 3 shows some results as example.

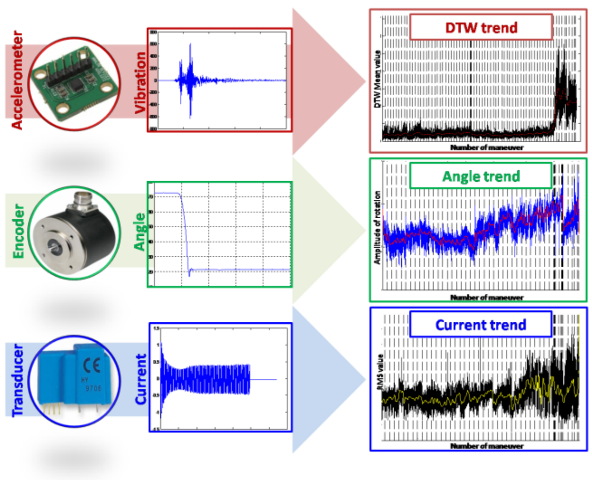

Fig 3. Feature extraction results

IV. DATA ANALYTICS

Feature extraction results are indexes and trends, representative of the operating conditions of the system, not always easy to interpret. The advent of high calculation powers has allowed the development of data analytics methodologies, able to extract empirical knowledge by statistical and machine learning tools [23]. Such knowledge is the starting point to identify fault detection rule, i.e. the critical condition whose occurrence triggers the maintenance intervention.

In literature several papers deal with diagnostic monitoring system, in which fault detection model is constructed through Pattern Recognition techniques, such as Clustering [24], Artificial Neural Network [25], Support Vector Machine [26], Decision Trees [27] and other methods. Such techniques require a great amount of data before being implementable, consequently their training results to be long and expensive [28].

To overcome previous limitations a simple fault detection method has been developed, using outlier detection rules. In particular 3-Sigma methodology has been applied to collected data, through the use of Shewhart Charts, also known as Control Charts. These techniques are used to check if a process is working in statistical control. The purpose is to detect any anomaly in the process: if a point is located outside Control Limits (UCL or LCL) then the process is out of statistic control and a malfunction probably occurred. The principle behind 3-Sigma rule consists in the fact that, when the process is in control, 99.73% of samples fall inside area bounded by Control Limits, positioned at 3 times the standard deviations from the mean. If a sample lies out of this range it is very likely that an anomaly have occurred[29].

Control Charts have been applied to experimental data relative to several CBs, in order to monitor aforementioned extracted features. Starting from diagnostic tool fault detection capability Fault Detection Accuracy (FDA) has been calculated on a sample of 18 devices. In particular, Control Charts are highly effective for mechanical damage, in which an FDA of 90% is observed, instead they are not a suitable tools for electrical faults, in which an FDA of 5% is obtained.

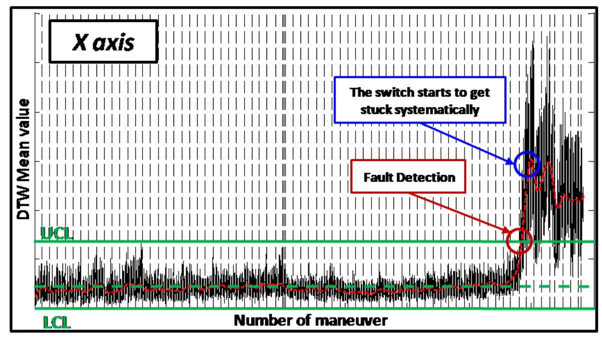

Fig. 4.Fault detection result

Fig. 4 shows the application of Control Charts to the accelerometric feature signal. In green Upper Control Limit (UCL) and Lower Control Limit (LCL) are reported. They are calculated initializing mean and variance values on a number of samples equal to the 20% of average CB useful life. LCL is equal to 0, since a negative DTW value is not possible. In black and red signal associated to the DTW distance, before and after an appropriate filtering, are represented. It is possible to notice that the Control Chart detects an anomaly in the system (red circle), just before the first occurrence of the systematic block of the CB (blue circle). This anomaly can be interpreted as a precursor of the malfunction that led to CB blocking, this conclusion has been confirmed by all experimental test, executed on different CBs.

V. CONCLUSION

In this work, a detailed study about condition monitoring of LVCB has been realized. On the basis of literature analysis, and practical considerations, a set of critical signals from maintenance point of view have been defined. In relation with the characteristics of those signals, a measurement setup has been developed in order to acquire all relevant LVCB weak signals its lifecycle. In parallel, a literature analysis in the field of features extraction has been conducted in order to select a set of methodologies that were further customized in order to obtain suitable tools for the specific application. In order to evaluate the goodness and applicability of these algorithms in this study, a preliminary measurement session and a starting test activity has been performed. Finally a fault detection system, based on the application Control Charts, is developed. The obtained results seem to validate the effectiveness of the developed diagnostic system for mechanical faults detection; instead it does not appear a reliable tool for electrical fault detection.

From an industrial perspective, the relevance of this approach can be easily understood by considering the increasing importance of Condition-Based Maintenance, as a maintenance policy able to predict and prevent catastrophic faults and to intervene only when necessary, in relation to the real conditions of the equipment, saving resources and increasing system availability.

REFERENCES

[1] V.Pesenti Campagnoni, S.Ierace, F.Floreani, S.Cavalieri, "A Pattern Recognition Methodology for Fault Detection: A Circuit Breaker Case Study", Proceedings of the 10th World Congress on Engineering Asset Management (WCEAM 2015), 2016, pp.279-287.

[2] L.Cristaldi, M.Faifer, S.Ierace, M.Lazzaroni, M.Rossi, "An approach based on electric signature analysis for photovoltaic maintenance", IEEE International Energy Conference and Exhibition (ENERGYCON 2012), 2012, pp.1-8.

[3] L.Fasanotti, S.Cavalieri, M.Tomasini, F.Floreani, S.Ierace, "Prognostics algorithms for Circuit Breaker application: a benchmark analysis", Industrial Informatics (INDIN), 2014 12th IEEE International Conference on. IEEE, 2014, pp.463-468.

[4] J.Lee, J.Ni, D.Djurdjanovic, H.Qiu, H.Liao, "Intelligent prognostics tools and e-maintenance", Computers in industry, vol.57, 2006, pp.476-489.

[5] A.K.S.Jardine, D.Lin, D.Banjevic, "A review on machinery diagnostics and prognostics implementing condition-based maintenance", Mechanical Systems and Signal Processing, vol.20, 2006, pp.1483-1510.

[6] S.Katipamula, M.R.Brambley, "Methods for fault detection, Diagnostics, and Prognostics for Building Systems - A Review, Part I", International Journal of HVAC and R Research, vol.11, 2005, pp.3-25.

[7] M.Marseguerra, E.Zio, L.Podofillini, "Condition-based maintenance optimization by means of genetic algorithms and Monte Carlo simulation", Reliability Engineering and System Safety, vol.77, 2002, pp.151-166.

[8] R.Kothamasu, S.H.Huang, W.H. VerDuin, "System health monitoring and prognostics - a review of current paradigms and practices", The International Journal of Advanced Manufacturing Technology, vol.28, 2006, pp.1012-1024.

[9] C.R.Heising, A.L.J.Janssen, W.Lanz, E.Colombo, E.N.Dialynas, "Summary of CIGRE 13.06 Working Group world wide reliability data and maintenance cost data on high voltage circuit breakers above 63 kV", Proc. 1994 IEEE Ind. Appl. Soc. Annu. Meet., 1994.

[10] M.Landry, S.Member, F.Léonard, C.Landry, R.Beauchemin, O.Turcotte, F.Brikci, A.D.System, "An Improved Vibration Analysis Algorithm as a Diagnostic Tool for Detecting Mechanical Anomalies on Power Circuit Breakers", Power Delivery, IEEE transactions on, vol.23, 2008, pp.1986-1994.

[11] L.Fumagalli, S.Ierace, M.Macchi, S.Cavalieri, "Assessment of industrial applicability of Electric Signature Analysis as diagnostic and prognostic tool", Proc. ESREL 2010 Annu. Conf., 2010.

[12] H.Johal, M.J.Mousavi, "Coil current analysis method for predictive maintenance of circuit breakers", IEEE/PES Transm. Distrib. Conf. Expo., 2008, pp.1-7.

[13] M.Runde, G.E.Ottesen, B.Skyberg, M.Ohlen, "Vibration analysis for diagnostic testing of circuit-breakers", IEEE Trans. Power Deliv., vol.11, 1996, pp.1816-1823.

[14] J.G.Hanse, "Honeywell MEMS inertial technology & product status", Position Location and Navigation Symposium, 2004 (PLANS 2004), 2004, pp.43-48.

[15] N.Rockmore, "The FFT: an algorithm the whole family can use", Comput. Sci. Eng., vol.2, 2000, pp.60-64.

[16] S.Chikkerur, A.N.Cartwright, V.Govindaraju, "Fingerprint enhancement using STFT analysis", Pattern Recognit., vol.40, 2007, pp.198-211.

[17] W. C. Lang, "Time-frequency analysis with the continuous wavelet transform", American Journal of Physics, vol.66, 1998, p.794.

[18] N.E.Huang, Z.Shen, S.R.Long, M.C.Wu, H.H.Shih, Q.Zheng, C.C.Tung,, H.H.Liu, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis", proc. of Royal Society of London A: Mathematical, Physical and Engineering Sciences, vol.454, No.1971, pp.903-955, 1998.

[19] A.Piyush Shanker, A.N.Rajagopalan, "Off-line signature verification using DTW", Pattern Recognit. Lett., vol.28, 2007, pp.1407-1414.

[20] O.Engineering, A.Arbor, "Automatic feature extraction of waveform signals for in-process diagnostic performance improvement", Journal of Intelligent Manufacturing, vol.12, 2001, pp.257-268.

[21] K. Zhu, "Fault Diagnosis of Rolling Bearings Based on IMF Envelope Sample Entropy and Support Vector Machine," J. Inf. Comput. Sci., vol.10, No.16, 2013, pp.5189–5198.

[22] V.J.Hodge, J. Austin,"A survey of outlier detection methodologies", Artificial Intelligence Review, vol.22, 2004, pp.85-126,.

[23] J.M.House, W.Y.Lee, D.R.Shin, "Classification techniques for fault detection and diagnosis of an 1999air-handling unit", ASHRAE Transactions, vol.105, 1999, pp.1087,.

[24] Y.Yu, C.Junsheng, "A roller bearing fault diagnosis method based on EMD energy entropy and ANN", Journal of sound and vibration, vol.294, pp.269-277.

[25] Y.Yu, Y.Dejie, C.Junsheng, "A fault diagnosis

approach for roller bearing based on IMF envelope spectrum and SVM", Measurement, vol.40, 2006, pp.953-950.

[26] B.S.Yang, M.S.Oh, A.C.C.Tan, "Fault diagnosis of induction motor based on decision trees and adaptive neuro-fuzzy inference", Expert Systems with Applications, vol.36, 2009, pp.1840-1849.

[27] Y.Zhao, B.Lehman, R.Ball, J.Mosesian, J.F.de Palma, "Outlier detection rules for fault detection in solar photovoltaic arrays", Applied Power Electronics Conference and Exposition (APEC), 2013 Twenty-Eighth Annual IEEE, 2013, pp.2913-2920.

[28] Z.A.Bakar, R.Mohemad, A.Ahmad, M.M.Deris, "A comparative study for outlier detection techniques in data mining", Cybernetics and Intelligent Systems, 2006 IEEE Conference on, 2006, pp.1-6.