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HIGH VOLTAGE CIRCUIT BREAKER VIBRATION SIGNATURE INDICES EVALUATION FOR CONDITION ASSESSMENT

PROCJENA STANJA VISOKONAPONSKIH PREKIDAČA BAZIRANA NA PARAMETRIMA VIBRACIJSKOG OTISKA

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Abstract: The importance of the high voltage circuit breaker for the power system's safe and reliable operation is paramount. This research aims to analyse and provide the most significant high voltage circuit breaker health state indices based on the non-invasive vibration fingerprint measurement method. Results obtained and presented in this paper are validated on the data set acquired from the vacuum circuit breaker.

Keywords: high voltage circuit breaker, vibration measurement, data acquisition

Sažetak: Važnost visokonaponskih prekidača za pravilan i pouzdan rad elektroenergetskog sistema je od enormnog značaja. Testiranje i praćenje vitalnih parametara prekidača osigurava pravovremenu reakciju u cilju sprečavanja potencijalnih problema. Osnovni cilj ovog istraživanja jeste evaluacija pokazatelja stanja prekidača dobijenih iz vibracijskog otiska u cilju klasifikacije stanja prekidača korištenjem mašinskog učenja. Dobijeni rezultati su evaluirani i demonstrirani na podacima dobijenim sa stvarnog visokonaponskog prekidača.

Ključne riječi: visokonaponski prekidači, mjerenje vibracija, akvizicija podataka

INTRODUCTION

The reliability advancement of the high voltage circuit breakers (HVCB) considering the design, arc quenching medium, or mechanical construction improves the power grid's reliability. However, the maintenance of the HVCB over its lifetime and exploitation is eminent. Several maintenance approaches are present nowadays, such as the traditional "Fail and Fix" approach, which is utilized only when a breakdown occurs, the "Predict and Prevent" approach combined with time-based maintenance or "Condition-based maintenance" [1].

Time-based maintenance defines periodic intervals for a check-up and testing of the HVCB what can lead to unnecessary intervention and even yield defects during the unnecessary operation of the HVCB [2]. On the other hand, predictive-based maintenance does not impose excessive HVCB operation. However, time-based maintenance requires an invasive approach, which represents testing the object in offline mode or "off the grid". This is a time-consuming process that usually induces power outages. For condition-based maintenance, the measurement procedure and method must not interfere with the regular operation of the HVCB [3]. To measure indices required for the condition assessment in a non-invasive manner, the vibration fingerprint measurement imposes itself as a promising approach.

The HVCB is an electromechanical device. In essence, a mechanical operation of the HVCB is serving an electrical purpose. In general, the HVCB consists of the following subassemblies: high voltage parts (arcing chamber, aux interrupters, insulation, etc.), electrical control and auxiliary (trip/close circuits, auxiliary switches, contactors, heaters, etc.), and operating mechanism (energy storage, actuators, damping devices, mechanical transmission, etc.) [4].

According to the Second international inquiry conducted by CIGRE during the years 1988 – 1991, that covered 132 utilities of 22 countries localize the operating mechanism as the weakest subassembly of the HVCBs with 43% of major failures (MF) and 44% of minor failures (mf) [5] (see Table I).

The mechanical nature of the HVCB results in the movement and collision of its subassemblies. All movement and collisions create series of superimposed percussion waves, which contains rich information about the health and condition of mechanical subassemblies of the HVCB [6], [7], [8]. The imperative is to obtain indices that would reliably reflect the condition of the HVCB.

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The approach of the HVCB condition assessment based on the vibration fingerprint measurement dates back to the late '80s and early '90s [9]. Research on indices extraction methods is widely spread among a wide pallet of approaches over three decades. The first group of indices is time-domain based indices such as short-time energy (STE), dynamic time warp (DTW), or statistical indices such as kurtosis, skewness, standard deviation, etc. [10], [11], [12]. The second group is the indices derived from the frequency or time-frequency domain. Those indices are mainly based on fast Fourier Transform (FFT), short-time Fourier transform (STFT), S transform (ST), or wavelet transform (WT) [13], [14]. The third group consists of methods that do not use previously mentioned methods as a base. In this group, the following methods can be included: local mean decomposition (LMD), empirical mode decomposition (EMD), ensemble empirical mode decomposition (EEMD), or variational mode decomposition (VMD) [15], [16], [6]. Very few authors in relevant literature address the HVCB condition assessment methods based on the chaos theory. Thus, the fourth group consists of methods based on indices derived from the chaos theory such as largest Lyapunov exponent (LLE), correlation dimension (CD), Kolmogorov entropy (KE) [17].

This paper is organized as follows: Section 1 provides insight on the HVCB health condition indices selection. Section 2 consists of the description of the evaluation and ranking criteria of the proposed indices. Validation of the best performing indices is demonstrated on the data set obtained on the real HVCB in Section 3.

Table I: Percentage of failures related to the subassembly responsible

Subassembly	MF (%)	mf (%)
High voltage parts	21	31
Electrical control and auxiliary	29	20
Operating mechanism	43	44
Other	7	5
Total	**100**	**100**

1. INDICES SELECTION

Despite the wide variety of indices used by the authors in the relevant literature, the selection of the promising indicators of the HVCB condition consists of the following: average power of the vibration signature, kurtosis, peak to root mean square (PRMS), signal to noise and distortion ratio (SINAD), skewness, signal-to-noise ratio (SNR), standard deviation, total harmonic distortion (THD), information entropy, the largest Lyapunov exponent giving the total of 10 indices. During the research, additional indices have been considered such as Kolmogorov-Sinai entropy, spectral entropy, spectral kurtosis etc. However, those parameters have yielded high computational intensity without increasing the classification performance.

Since the vibration signature reflects the mechanical state and potential issues, and based on the fact that it is not imperative to localize in time-frequency domain potential malfunction, the statistical time-based indices are used as a starting point. Transfer of the energy from the energy storage (loaded spring or hydraulic operating mechanism) via linkage to the moving contacts of the HVCB implies the transfer of the energy [18]. Due to any potential issue in the linkage, the transfer of the energy will differ from the healthy operation. Driven by this statement, the average power is selected as the first indicator since the change of the energy transfer will be embedded into a signature and implicitly into the signal's average power. The malfunction in the form of additional renounces of the moving contacts will result in a higher spread of the vibration signature signal related to the mean version. For this reason, the standard deviation, SNR, and SINAD indices have been chosen. To minimize the computation intensity, but to include the potential issue's influence on the spectrum, the THD indicator is included in the list. The information entropy is a measure of the disorder for a system. For our particular case, it is an accurate measure of the complexity of the vibration signal (e.g., amplitude, phase, frequency, and energy distribution of the vibration signal changing with different fault types) [19]. This makes Information entropy a promising candidate for the HVCB condition assessment. The largest Lyapunov Exponent (LLE) is widely used in the rotating machines condition assessment [20], asteroidal objects motion [21] or study of pathological locomotion [22]. In essence, the LLE uses reconstruction vectors or phase space as the input matrix to identify the existence and to measure the degree of non-linearity of the time series data [23]. In essence, the LLE is the indicator of the presence of chaos in the system or its sensitivity to the initial conditions. Thus, this set the LLE high on the list of promising indices for the HVCB condition assessment.

2. PERFORMANCE EVALUATION

2.1. Evaluation Criteria

As stated in the previous section, the following indices have been considered for the performance analysis: average power, Lyapunov exponent, information entropy, kurtosis, PRMS, SINAD, skewness, SNR, standard deviation, and THD. The evaluation of the indices is based on the higher distinction between "*good*" and "*need to investigate*" vibration signatures of HVCB.

As a performance index, mutual information has been used. Mutual information is a quantifier of the variable's statistical mutual dependence [24]. The term "mutual information" (MI), also known as "*transinformation*", was first introduced in a classical information theory by Shannon in 1948. In essence, it is a non-parametric measure of relevance that measures mutual dependence of two variables, both linear and non-linear, for which it has a natural generalization. For two discrete variables $X=[x_1,x_2,\ldots,x_n]$ and $Y=[y_1,y_2,\ldots,y_m]$, the mutual information is calculated as a sum:

$$I(X:Y)=\sum_{i,j} p(x_i,y_j)\log\left(\frac{p(x_i,y_j)}{p(x_i)\,p(y_j)}\right)$$

where $p(x_i,y_j)$ is the joint probability mass of X and Y while $p(x_i)$ and $p(y_j)$ are the marginal probability mass of X and Y respectively [25].

2.2. Evaluation Process

For the evaluation purpose, a set of 2530 vibration signatures have been analysed. The first subset of 1265 signatures are obtained on the healthy HVCB with all parameters within the ones recommended by the manufacturer. Those signatures in this subset are labelled as "*good*".

Another subset of 1265 signatures are recorded on the same HVCB after a large number of operations, and with the vital parameters of closing or opening time outside of the ones recommended by the manufacturer. These subset signatures are labelled as "need to investigate". For both subsets, selected indices have been calculated and analysed. Hence, we plotted the obtained values, the first 1265 values are for "*good*" signals, and the last 1265 are for "*need to investigate*" values. The plots are shown in Figure 1. Analysing plotted and calculated values of the indices, it can be concluded that the mean value between "*good*" and "*need to investigate*" signals are distinguishable. In figure 1, the mean value of the parameter values over different HVCB operations for the "*good*" vibration signature is marked with a green line, and for the "*need to investigate*", the vibration signature is marked with a pink line. Also, it is noticeable that values are dispersed.

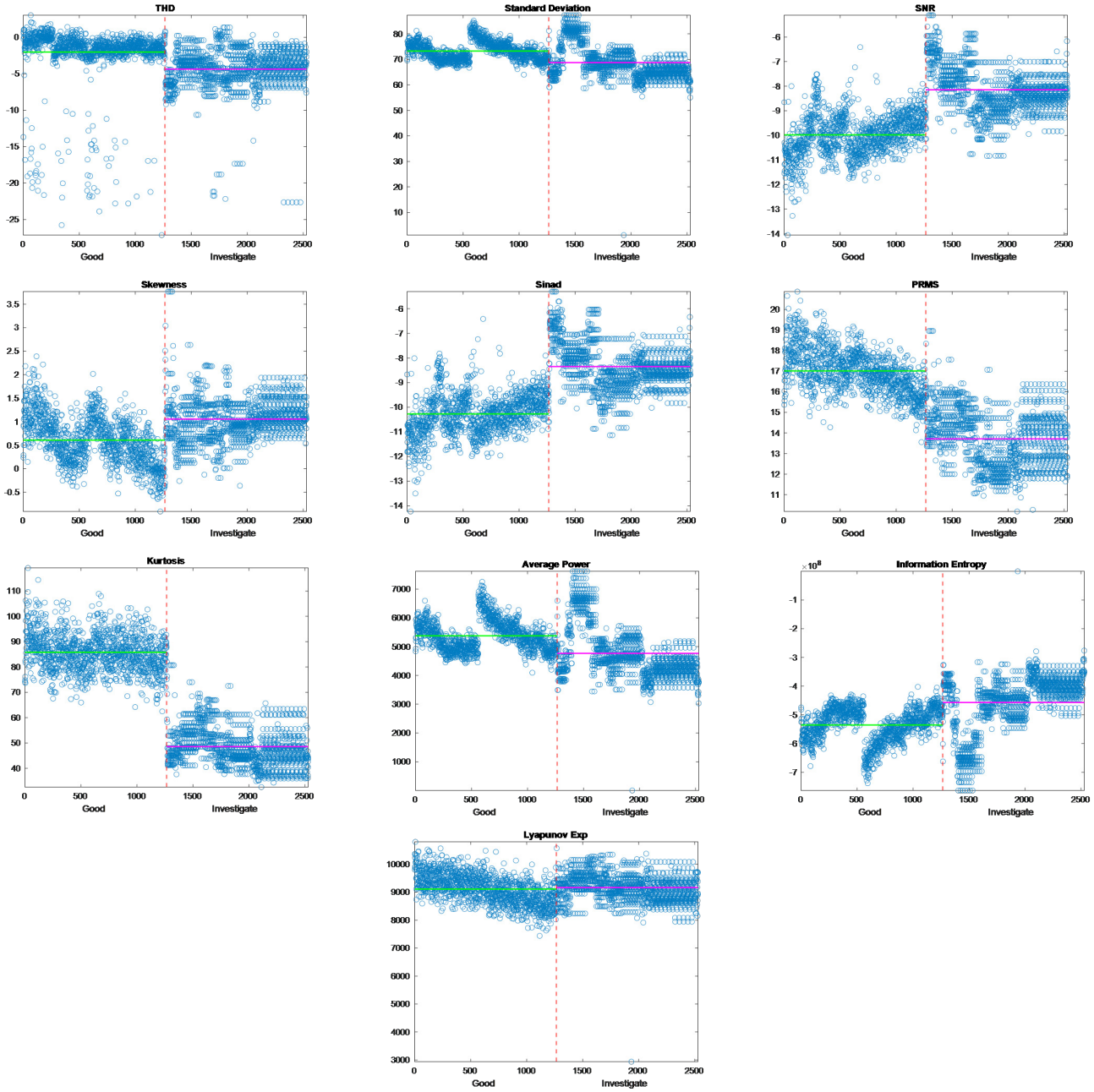


Figure 1: The mean value of selected indices for "*good*" and "*need to investigate*" class

To provide the quantification of how well classes are separable, mutual information has been used for each indicator. Consider that the vector $F=[f_1,f_2,...,f_n]$ is the vector of indicator calculated values for the n vibration fingerprints while the vector $C=[c_1,c_2,...,c_n]$ is the vector of classes "*good*" or "Investigate" denoted as a 1 or 0, respectively. If the vector C truly reflects the state of the HVCB for the corresponding vibration signature or the indices vector F, then the mutual information as a measure of relatedness between two variables will take higher values. The mutual information values for the set of selected indices are given in Table II.

Table II: Mutual information of the selected indices and corresponding classes

Ranking	Indicator	MI
1	Kurtosis	0.6682
2	PRMS	0.5719
3	SINAD	0.4779
4	SNR	0.4727
5	THD	0.4634
6	Information entropy	0.4339
7	STD	0.4232
8	Average power	0.4229
9	Skewness	0.2933
10	Lyapunov Exp	0.2879

The parameters that are initially considered as most promising, such as information entropy and largest Lyapunov exponent have been ranked in 6th and 10th place, respectively. Nevertheless, the vibration signatures have been labelled based on the main contact timing and contact motion stroke thus the classification presented in the next section with achieved performance in terms of accuracy, sensitivity and specificity highly coincide with the methods defined by the standards, and used in the industry for decades.

However, the question of how many of the indices ranged at the top of the Table II will be sufficient for the high-performing machine learning classification algorithm. This question will be addressed in the next section. Thus, the timeline of the evaluation and experimental phase is organized as:

- Rank indices based on mutual information,
- Create 10 sets adding 1 additional indicator in each following the indices ranking,
- Train machine learning classification algorithms for each set,
- Obtain classification algorithm accuracy, sensitivity, and specificity for each algorithm throughout each set.

3. EXPERIMENTAL RESULTS

To provide the answer to the question of how many selected indices will yield high-performing classification whether the HVCB is in good condition or needs to be investigated, the machine learning algorithms will be trained and tested on real data.

The data for the model are the true vibration signatures of the HVCB obtained experimentally. The object under test has been an ABB SACE 2 EMAX high voltage circuit breaker family member. The vibration signature signals have been recorded using a PR MEMS (piezoresistive micro electromechanical system) mono-axial accelerometer placed on the chassis of the HVCB. A total of approximately 42000 complete cycles of the de-energized HVCB consisted of open operation, charge spring, and close operation. The experiment has been started on the brand new HVCB until its failure. For the sake of clarity and computation intensity, the closing operation has been considered.

Obtained vibration signatures are classified as "*good*" or "*need to investigate*" according to the closing or the opening time recommended by the manufacturer, as well as a stroke parameter of the moving contact trajectory. As recommended in the Maintenance guide by the manufacturer of the tested HVCB, closing time higher than 65.0 ms or lower 56.0 ms yields potential investigation of the HVCB condition.

The distribution of the calculated closing time values is shown on the histogram in Figure 2. The closing time and motion stroke parameters have been obtained using a DV Power circuit breaker analyser and timer (CAT). The signals acquired for those calculations are sampled at the rate of 20 kHz, while vibration signature signals are sampled at the rate of 33 kHz.

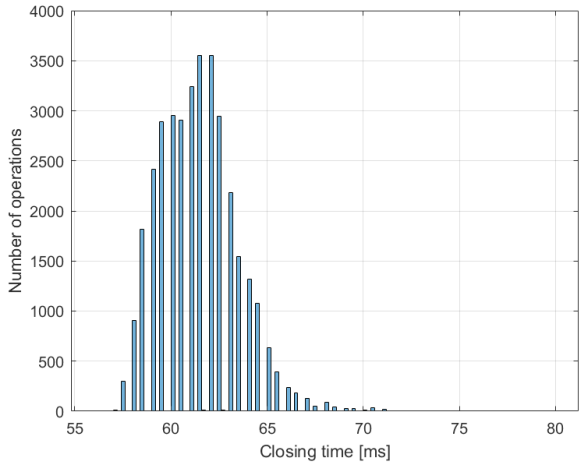


Figure 2: Closing time values distribution

This indicates that the set is not well balanced since there is a quite small part of the results that are not within limits specified by the manufacturer. Precisely, the "*good*" class results take 96.44% of the results dataset while the "need to investigate" class takes only 3.56%. In order to prepare data for the machine learning algorithm, the data set has been balanced using Synthetic Minority Over-Sampling Technique (SMOTE) [26]. Thus, a total of 34295 healthy HVCB vibration sig-

natures and another 34290 vibration signatures of the HVCB with closing time and stroke parameters outside of the recommended limits have been used for training and indices calculation. The training of the classification algorithm has been performed based on 5-fold cross-validation.

The training of the algorithms has been conducted by stepping up the indices used, starting with the single one ranked first in Table II adding one more indicator in each successive step. This forms 10 Sets of indices, as shown in Table III. The approach of stepping up the sets intends to obtain the required number of indices for which the classification algorithm will provide satisfactory results utilizing minimal computational intensity. Since this approach and selection of indices is unique considering methods available in relevant literature, there is no referent performance of the classification algorithm to compare with.

Table III: Indices sets used for testing machine learning classification algorithms

Set	Features
Set 1	Kurtosis
Set 2	Set 1 + PRMS
Set 3	Set 2 + SINAD
Set 4	Set 3 + SNR
Set 5	Set 4 + THD
Set 6	Set 5 + IE
Set 7	Set 6 + STD
Set 8	Set 7 + Average power
Set 9	Set 8 + Skewness
Set 10	Set 9 + LLE

The following classification algorithms have been tested: linear discriminant, quadratic discriminant, logistic regression, Gaussian Naive Bayes, kernel naive bayes, linear SVM, quadratic SVM, cubic SVM, fine Gaussian SVM, coarse Gaussian SVM, ensemble bagged trees, ensemble subspace discriminant, ensemble subspace KNN, fine KNN, weighted KNN, cubic KNN. The best-performing algorithms regarding accuracy among 16 tested algorithms are fine k-nearest neighbour (Fine KNN), weighted k-nearest neighbour (Weighted KNN) and cubic k-nearest neighbour (Cubic KNN). Other algorithms, besides the three top performers, yield accuracy ranging from 42.2% for the Cubic SVM up to 95.9% for the Ensemble Bagged Trees. Additional valuable performance indicators derived from the confusion matrix, besides accuracy, are specificity and sensitivity and they will be considered along with the accuracy. As the best-performing algorithms for all feature sets, detailed insight into the performance of the Fine KNN, Weighted KNN and the Cubic KNN algorithm are presented in Table IV, V and VI, respectively.

Table IV: Performance of the Fine KNN classification algorithms on different indices sets

	Indices set	Accuracy [%]	Sensitivity [%]	Specificity [%]
Fine KNN	Set 1	84.4	82.3	81.4
	Set 2	91.2	90.1	91.2
	Set 3	96.5	95.3	97.6
	Set 4	97.2	95.8	98.5
	Set 5	97.8	96.4	99.1
	Set 6	98.5	97.4	99.6
	Set 7	98.2	97.1	99.6
	Set 8	98.4	97.3	99.7
	Set 9	98.8	97.9	99.8
	Set 10	98.9	98.0	99.9

Table V: Performance of the Weighted KNN classification algorithms on different indices sets

	Indices set	Accuracy [%]	Sensitivity [%]	Specificity [%]
Fine KNN	Set 1	85.3	88.3	82.4
	Set 2	91.5	92.1	91.0
	Set 3	96.1	94.5	97.7
	Set 4	96.6	94.8	98.4
	Set 5	97.2	95.2	99.1
	Set 6	97.8	95.9	99.6
	Set 7	97.8	95.9	99.7
	Set 8	97.8	95.8	99.7
	Set 9	98.2	96.6	99.8
	Set 10	98.2	96.4	99.9

Table VI. Performance of the Cubic KNN classification algorithms on different indices sets

	Indices set	Accuracy [%]	Sensitivity [%]	Specificity [%]
Fine KNN	Set 1	82.7	88.4	77.2
	Set 2	88.2	89.9	86.5
	Set 3	93.3	91.8	94.8
	Set 4	94.3	92.2	96.3
	Set 5	95.0	92.7	97.4
	Set 6	96.1	93.2	98.9
	Set 7	96.2	93.4	99.0
	Set 8	96.2	93.4	98.9
	Set 9	96.8	94.1	99.5
	Set 10	96.9	94.2	99.7

It is evident that all tree performance indices (accuracy, sensitivity, and specificity) for all three classification algorithms have a rising trend as the new features are included. To visualize these numbers, consider Figures 3, 4 and 5.

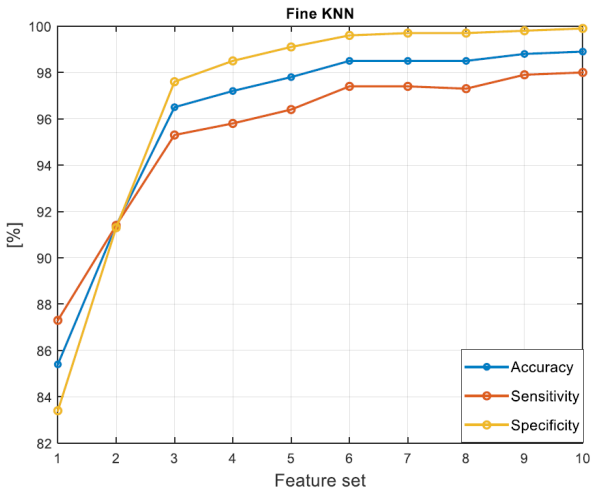


Figure 3: Fine KNN performance using different indices set

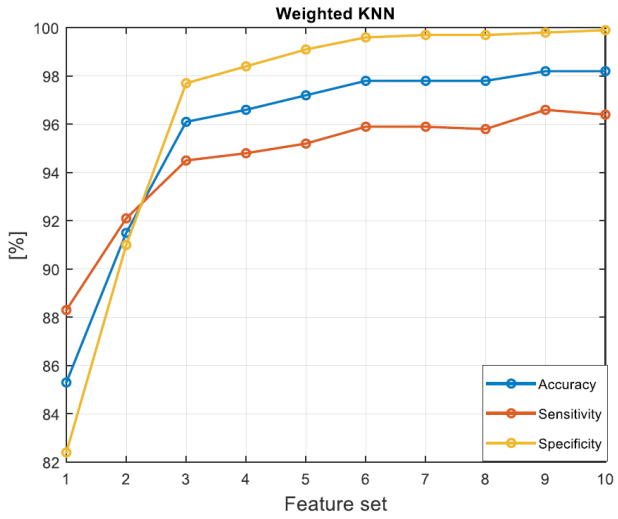


Figure 4: Weighted KNN performance using different indices set

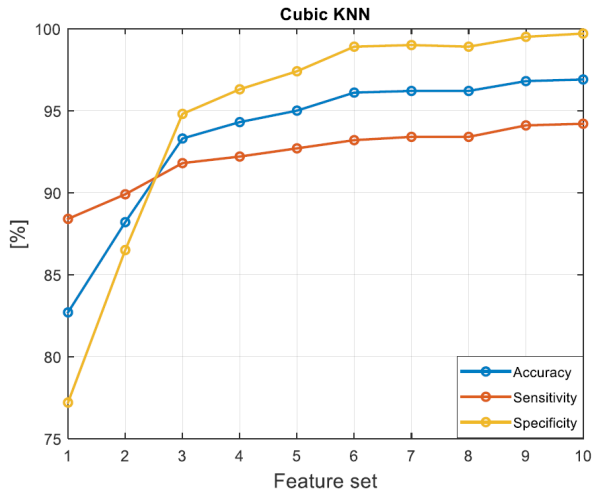


Figure 5: Cubic KNN performance using different indices set

For all three algorithms, the highest performance change is between using Set 3 and Set 4. However, additional indices besides Set 6 do not yield high-performance change compared to the computation cost. All experiments have been conducted in the MATLAB R2021a environment.

4. CONCLUSION

Based on the obtained results, it is evident that the proposed indices are good candidates for the condition assessment of the HVCB. This statement is supported by the experimental validation based on the vibration signatures signals obtained from the HVCB. Also, ranking of the most influential indices for the machine learning classification algorithm using mutual information as a base has been performed, tested and validated.

However, the proposed indices and classification algorithms are tested and validated on only one type of HVCB. Considering the nature and origin of the vibration on the HVCBs in general, this approach should apply to any of the HVCB. However, this statement should be confirmed by extended testing on different types of the HVCB as a part of future work. Furthermore, for the test data obtained from different types of the HVCB, the comparison of the prediction for different parameters set of the same size along with the stepping up approaches used in this paper will be evaluated.

REFERENCES

[1] L. Fasanotti, S. Cavalieri, M. Tomasini, F. Floreani and S. Ierace: Prognostics algorithms for circuit breaker application: A benchmark analysis, in International Conference on Industrial Informatics, INDIN 2014, 2014

[2] D. Lee, B. Lithgow and R. Morrison: New fault diagnosis of circuit breakers, IEEE Transactions on Power Delivery, vol. 18, no. 2, pp. 454-459, 2003

[3] Y. Zhang, Y. Jiang, Y. Chen and Y. Zhang: Fault Diagnosis of High Voltage Circuit Breaker Based on Multi-classification Relevance Vector Machine, Journal of Electrical Engineering and Technology, no. 15, pp. 413-420, 2020

[4] A. Janssen, D. Makareinis and S. Carl-Enjar: International Surveys on Circuit-Breaker Reliability Data for Substation and System Studies, IEEE Transaction on Power Delivery, vol. 29, no. 2, pp. 808-8014, 2014

[5] CIGRE Working Group 13.06: Final report ofthe second international enquiry on high voltage circuit-breaker failures and defects in service, CIGRE Tech. Brochure 83, June 1994

[6] K. Obarcanin, B. Lacevic, M. Ermidoro: A High-Voltage Circuit Breaker Condition Assessment Method using the Vibration Fingerprint based on VMD-EM method, in IEEE International Instrumentation and Measurement Technology Conference (I2MTC), Dubrovnik, Croatia, 2020

[7] A. Secic and K. Obarcanin: Power circuit breaker condition assessment based on vibration fingerprint measurement and why it can save your day, NETA World Magazine, pp. 89-95, 2017

[8] Y. Zhang, Y. Shao, W. Gong, Z. Zhang, J. Wu: Research on combined diagnosis of mechanical fault vibration-sound signal of high voltage circuit breaker based on EEMD-energy entropy feature, in International Conference on Sensors and Instruments 2021, Qingdao, China, 2021

[9] L. Mingliang, W. Keqi, S. Laijun, Z. Jianfeng: A New Fault Diagnosis Method for High Voltage Circuit Breakers Based on Wavelet Packet and Radical Basis Function Neural Network, Open Cybernetics & Systemics Journal, vol. 8, pp. 410-417, 2014
[10] Q. Yang, J. Ruan, Z. Zhuang, D. Huang: Fault Identification for Circuit Breakers Based on Vibration Measurements, IEEE Transactions on Instrumentation and Measurement, vol. 69, no. 7, pp. 4154 - 4164, 2019
[11] M. Wong, L. Jack, A. Nandi: Modified self-organising map for automated novelty detection applied to vibration signal monitoring, Mechanical Systems and Signal Processing, vol. 20, no. 3, pp. 593-610, 2006
[12] M. Landry, F. Léonard, C. Landry, R. Beauchemin, O. Turcotte, F. Brikci: An improved vibration analysis algorithm as a diagnostic tool for detecting mechanical anomalies on power circuit breakers, IEEE Transactions on Power Delivery, vol. 23, no. 4, pp. 1986-1994, 2008
[13] Y. Yeap, A. Ukil: Fault Detection in HVDC System Using Short Time Fourier Transform, in IEEE Power and Energy Society General Meeting (PESGM), 2016
[14] N. Charbkeaw, T. Suwanasri, T. Bunyagul: Mechanical Defect Detection of SF6 High Voltage Circuit Breaker Using Wavelet Based Vibration Signal Analysis, in 5th International Conference on Electrical EngineeringElectronics Computer Telecommunications and Information Technology, 2008
[15] H. Nantian, F. Lihua, C. Huowei, X. Dianguo, C. Huaijin, N. Yonghui: Mechanical Fault Diagnosis of High Voltage Circuit Breakers with Unknown Fault Type Using Hybrid Classifier Based on LMD and Time Segmentation Energy Entropy, Entropy, vol. 18, no. 9, pp. 322 - 341, 2016
[16] Z. Jianfeng, L. Mingliang, W. Keqi, X. Jingyan, S. Shuli: Feature extraction of HV circuit breaker based on ensemble empirical mode decomposition and correlation dimension, in Electronic Measurement & Instruments (ICEMI), 2015 12th IEEE International Conference on, 2015
[17] Q. Yang, J. Ruan, Z. Zhuang, D. Huang: Chaotic Analysis and Feature Extraction of Vibration Signals from Power Circuit Breakers, IEEE Transactions on Power Delivery, vol. 35, no. 3, pp. 1124-1135, 2019
[18] M. Kapetanovic, High Voltage Circuit Breakers, Sarajevo: Faculty of Electrical Engineering Sarajevo, 2011
[19] Q. Yang, J. Ruan, Z. Zhuang, D. Huang, Z. Qiu: A New Vibration Analysis Approach for Detecting Mechanical Anomalies on Power Circuit Breakers, IEEE Access, vol. 7, pp. 14070 - 14080, 2019
[20] W. Caesarendra, P. Kosasih, A. Tieu, C. Moodie: Application of the largest Lyapunov exponent algorithm for feature extraction in low speed slew bearing condition monitoring, Mechanical Systems and Signal Processing, vol. 50, no. 51, pp. 116-138, 2015
[21] C. Froeschlé, E. Lega and R. Gonczi: Fast Lyapunov Indicators. Application to Asteroidal Motion, Celestial Mechanics and Dynamical Astronomy, vol. 67, no. 1, pp. 41-62, 1997
[22] A. Ekizos, A. Santuz, A. Schroll, A. Arampatzis: The Maximum Lyapunov Exponent During Walking and Running: Reliability Assessment of Different Marker-Sets, Front. Physiol., vol. 9, 2018
[23] B. R. Hunt, J. A. Kennedy, T.-Y. Li, H. E. Nusse: The Theory of Chaotic Attractors, New York: Springer Science+Business Media, 2004
[24] A. Fraser, H. Swinney:Independent coordinates for strange attractors from mutual information, Physical Review A, vol. 33, no. 2, pp. 1134-1140, 1986
[25] J. Walters-Williams, Y. Li: Estimation of mutual information: A survey, in Rough Sets and Knowledge Technology, vol. 23, Berlin, Heidelberg, Springer, pp. 389-396, 2009
[26] N. V. Chawla, K. W. Bowyer, L. O. Hall, W. P. Kegelmeyer: SMOTE: Synthetic Minority Over-sampling Technique, Journal of Artificial Intelligence Research, vol. 16, pp. 321-357, 2002
[27] J. Taylor: Introduction to error analysis, the study of uncertainties in physical measurements, 1997.
[28] J. Taylor, Introduction to error analysis, the study of uncertainties in physical measurements, University Science Books, 1997
[29] P. Schober, C. Boer, L. Schwarte, "Correlation Coefficients, Anesthesia & Analgesia, vol. 126, no. 5, p. 1763–1768, 2018

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