DOI: 10.2507/35th.daaam.proceedings.xxx

# INFORMATION ENTROPY BASED DIAGNOSTICS OF MECHANICAL SYSTEMS

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**This Publication has to be referred as:** Neusser, Z[denek] (2024). Information Entropy Based Diagnostics of Flexible Mechanical Systems, Proceedings of the 35th DAAAM International Symposium, pp.xxxx-xxxx, B. Katalinic (Ed.), Published by DAAAM International, ISBN 978-3-902734-xx-x, ISSN 1726-9679, Vienna, Austria
DOI: 10.2507/35th.daaam.proceedings.xxx

**Abstract**

The article deals with the problem of fault diagnosis of mechanical systems. The traditional approach is based on the evaluation of the change of physical parameters of the system based on identification. Such an approach often fails due to various stochastic excitations of the system. This paper describes a different approach based on computational information entropy. Information entropy does not lead directly to the identification of physical parameters, but it can distinguish between the behaviour of the original system and the system with changed physical parameters due to some failure. Another advantage of information entropy is that it provides a single value for detecting changes in the physical parameters of a mechanical system. This approach is particularly advantageous for OMA (operational modal analysis) of elastic mechanical systems where the identification encounters the problem of knowing the excitation.

**Keywords:** Structural Health monitoring; Predictive maintenance; Non-destructive testing

## 1. Introduction

Structural health monitoring and fault detection are important tools in the modern approach to predictive maintenance. Structural damage to these structures can cause production losses, cause machinery failure or even injury to operators. There are many applicable methods for detecting and locating structural damage. However, the measurement procedure is usually complex, expensive sensors are required and often only local information about the structure is provided.

Natural frequencies, natural modes and associated damping usually represent mechanical properties of the structure. There are several ways to predict and obtain these parameters. The usual way is to perform a modal analysis. The system is excited by some input (usually a hammer blow or a harmonic function with a certain frequency range or white noise). The response of the system is measured at several points, which requires the preparation of an experiment, the experiment itself is time consuming, and data processing follows. Unlike modal analysis, operational modal analysis does not use a specific system input. Excitation is provided by natural and ambient vibrations under its operating conditions (machine motors, external faults, etc.). The analysis requires long-term measurements but does not require expensive measuring equipment. A sufficient level of excitation of the structure is required.

Traditional methods are based on mathematical analysis of modal parameters (natural frequencies, mode shapes and modal damping) [1], [2], [3], [4], [5]. These methods assume that structural damage affects the location/shape of modal parameters (usually natural frequencies, which can be easily obtained). As stated by Salawu [6], eigenfrequency analysis inherently suffers from low sensitivity to change and requires at least a 5% change in the locations of the eigenfrequencies to effectively detect the occurrence of damage. Mode shape analysis shows better sensitivity to damage but is still subject to noise generated by ambient frequency generators (e.g. wind, cars, etc.), leading to many false positives [7]. Mode shapes are also difficult to detect in large structures and are dependent on the number and location of vibration sensors [8]. Modern vibration analysis methods use frequency response function (FRF) usually in conjunction with principal component analysis (PCA), deep principal component analysis (DPCA) [9] using deep learning models and artificial neural networks (ANN) [10], [11], [12], [13], [14]. While PCA-ANN methods are effective in detecting even small structural damage with good accuracy in a noise-free/very low noise environment (less than 2\% [15] or less than 5\% [13] noise), they still fall short of accuracy when significant noise is added to the input data [16]. These methods are also complex and require many adjustments regarding the number of principal components (PCs) of the FRF (or FRF adjustment using cepstrum [17], [18]) that are chosen as input to the ANN, and optimization of the parameters of the ANN itself. State space reconstruction using multi-scale analysis is presented in [19].

This paragraph describes the cross-entropy approach [20], which includes a wide range of methods as presented in [21]. In [22], [23], [24], cross-entropy is applied to the measured signal but with a different state indicator for further evaluation. Eigenmode evaluation with cross-entropy support in [25], [26] performs multi-point measurements. The papers [27], [28], [29] uses cross entropy in data processing with the following optimization. Our research, unlike those papers, uses the behaviour of cross-entropy as a direct indicator of structural change.

Our work presents an operational method inspired by modal analysis that seeks frequency change to indicate structural changes. The presented method based on cumulative cross-entropy slope comparison clearly distinguishes between the original and the altered structure, even with very low signal-to-noise ratio. The method is applied to the one mass system with its eigenfrequency alteration.

## 2. Problem formulation

Typical measurement of mechanical system is usually subject to error due to noise in the signal. Frequency analysis of such a signal has the problem of correctly determining the eigenfrequencies. Let’s introduce one-mass one degree of freedom system with known eigenfrequency. The system is excited by random signal.

The mechanical system on the **Error! Reference source not found.** has mass *m*, spring stiffness *k* and external force *F* exciting the system. The excitation force brings disturbance into the system. It is chaotic, noisy signal characterised as white noise. Measured, output signal is mass position. The system has prescribed eigenfrequency $\omega$ and mass *m*, the spring stiffness is than obtained using (1).

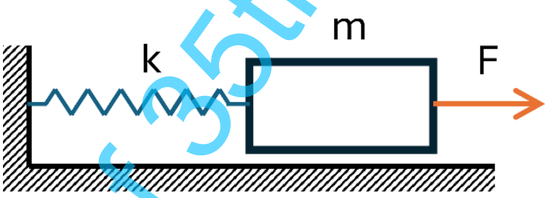


Fig. 1. One-mass model

$$k = m\omega^2 \tag{1}$$

Example of input signal and its frequency spectrum is presented in the

Fig. 2. Such a signal could represent a chaotic excitation of the system, being suitable for operational modal analysis.

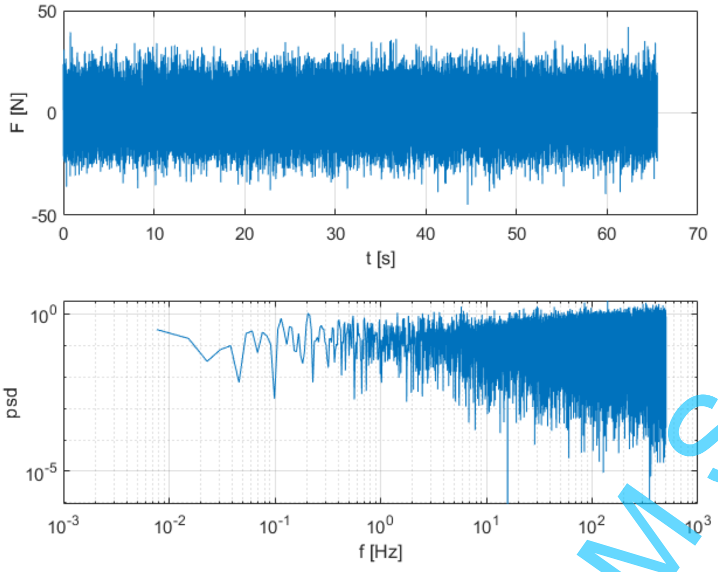


Fig. 2. Input signal - white noise and its frequency spectrum

For mass equal to 1 kg and eigenfrequency at 3 Hz the system response to white noise input signal from Fig. 2 is shown in the Fig. 3.

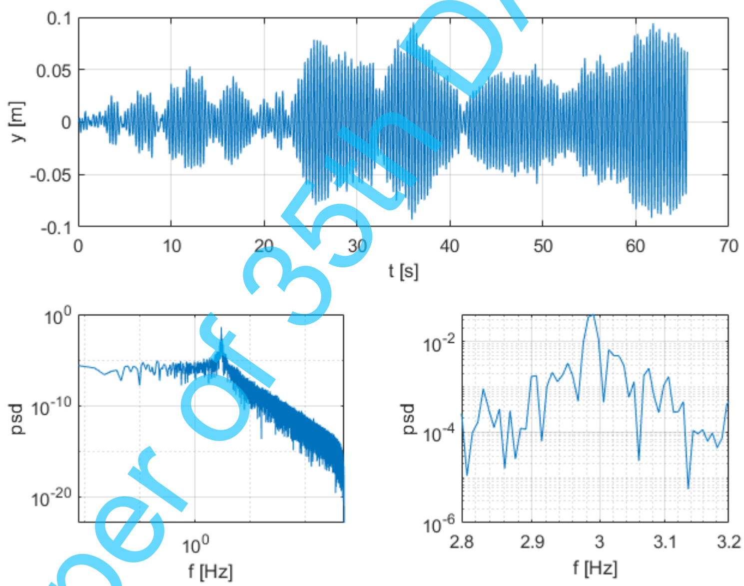


Fig. 3. Signal output - time behaviour and its frequency spectra with detail nearby eigenfrequency

The system output frequency analysis is depicted in the Fig. 3 at the bottom. On the left the overall spectra is shown, on the right the zoom in the surrounding of eigenfrequency is depicted. It is obvious that frequency analysis does not match the correct value. This problem is going to be overcome our entropy based diagnostics approach.

## 3. Proposed method

The proposed diagnostic method belongs to the group of operational modal analysis methods. The measured data are pre-processed using normalization to emphasis the peak frequencies in the signal, the data are averaged from more measurements and finally compared with reference data using cross entropy function. The whole procedure is shown in the Fig. 4.

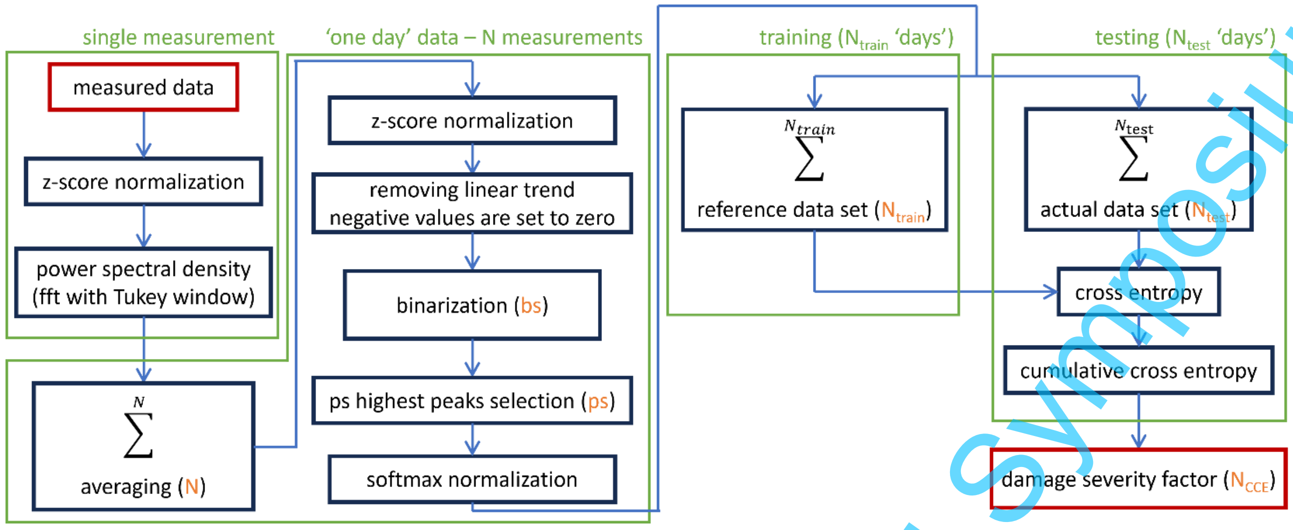


Fig. 4. Proposed method workflow

The individual measured signals are first normalized by z-scores in the time domain, followed by conversion to the frequency domain - power spectral density calculation with window function. This is followed by averaging of *N* measurements, which could be called "one day" data. The obtained signal is z-score normalized, then the linear trend is removed from the signal and finally all negative values are set to zero. So called binarization is performed in the next step. Every *bs* adjacent frequencies are averaged into one value – so called bin. Then the *ps* highest values are taken for further investigation, the rest is zero. The last, but important operation is performed – the softmax normalization, see (2).

$$s = \frac{e^{\text{signal}}}{\sum e^{signal}} \tag{2}$$

Variable *signal* in (2) represents the frequency behaviour of peaks in binarized spectra, variable *s* represents its softmax normalization behaviour. Obtained data could enter two following phases. At first, the training phase, where the reference data set is obtained, created by $N_{train}$ softmax spectra averaged data ($a_{ref}$). At second follows the testing phase, where the actual data set is created by $N_{test}$ softmax spectra averaged data ($a_j$). Then the cross-entropy is evaluated.

$$H_j = -\sum_{i=1}^{N_{bin}} a_{ref}(i)\log a_j(i) \tag{3}$$

The cross-entropy value $H_j$ is obtained by summarizing the values in (3) over the number of binarization points $N_{bin}$. Cumulative cross-entropy behaviour is created by adding the actual cross-entropy value to previous cumulative cross-entropy value. Relative damage severity factor $d\alpha_i$ is evaluated as a comparison of cumulative cross-entropy slopes $\alpha_i$, with $\alpha_1$ corresponding to slope of training data, see (4).

$$d\alpha_i = \frac{\alpha_i - \alpha_1}{\alpha_1} \tag{4}$$

## 4. Method application

The one mass system is subject to white noise excitation. The system has prescribed eigenfrequency equals to 3 Hz. The training is performed and follows the testing phase. At certain point, the eigenfrequency is changed to 3.01 Hz and finally follows the change to 3.02 Hz, imitating the structural changes.

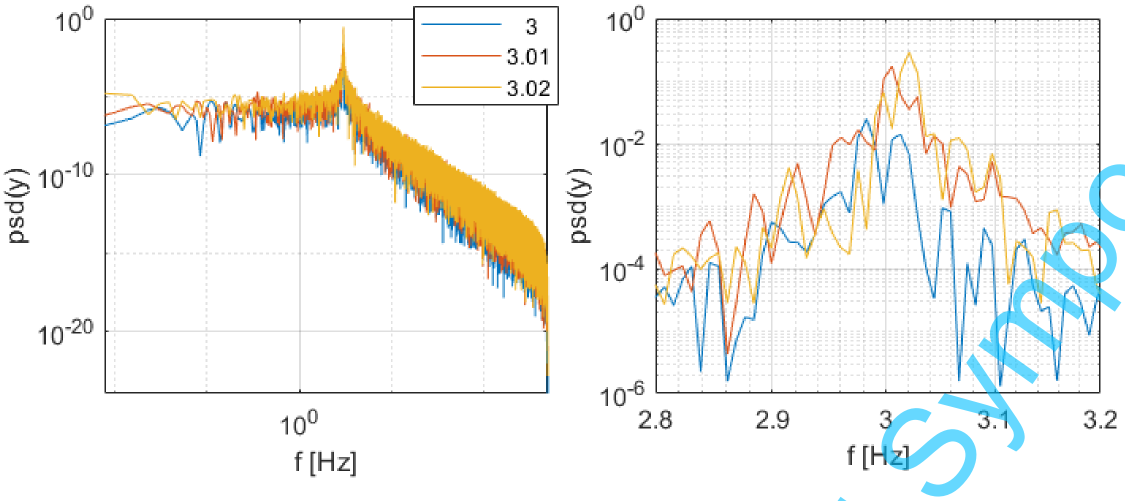


Fig. 5. Frequency responce for different system eigenfrequency, four signals averaged

Fig. 5 shows the problem of eigenfrequency recognition. In this case, all signals are averaged from four measurements. The eigenfrequency at 3.02 Hz is recognized clearly, 3 Hz and 3.01 Hz are hard to determine. Approach, we are presenting, uses method of signal averaging together with presented normalization and cross-entropy measure to clearly distinguish between the original system behaviour and altered structure behaviour.

| N | bs | ps | $N_{train}$ | $N_{test}$ | $N_{CCE}$ |
|---|---|---|---|---|---|
| 2 | 1 | 10 | 4 | 1 | 1 |

Table 1. Procedure parameters settings

The procedure settings are presented in the

Table 1. There are two signals averaged for so called one day measurement (see Fig. 4), binarization is unapplied, maximal number of selected peaks is 10, training phase is performed over four ‘day’ measurements and testing is evaluated at every “day” measurement. Slope is calculated from one adjacent (previous) point.

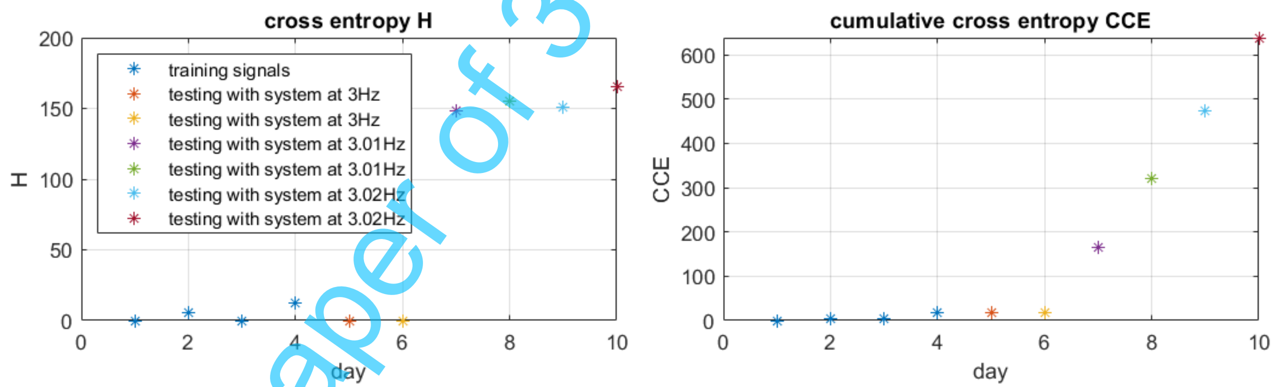


Fig. 6. Cross entropy and cumulative cross entropy behaviour

There is performed 8 training simulations with system 3 Hz eigenfrequency and 12 testing simulations. First four testing simulations are with system eigenfrequency at 3 Hz, next four simulations with system eigenfrequency 3.01 Hz and last four simulations with system eigenfrequency 3.02 Hz. The Fig. 6 shows on the left cross entropy behaviour, at fist for data from training signals, followed by the testing data. Cross entropy with altered system eigenfrequency shows much higher values than original system cross entropy evaluation. On the right of Fig. 6 is presented cumulative cross entropy behaviour. It is obvious, that slope with original system differs considerably in comparison to the slope of system with altered eigenfrequency.

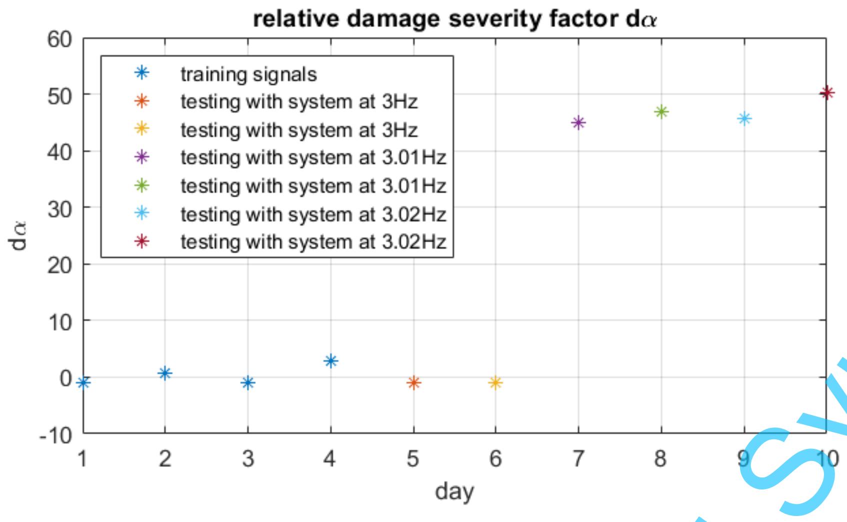


Fig. 7. Relative damage severity factor behaviour

Relative damage severity factor in Fig. 7 is the indicator of mechanical structure condition. There is obvious value difference between the sixth and seventh evaluated measurement "day".

## 5. Conclusion

In this paper, the problem of fault diagnosis of mechanical systems based on the evaluation of the identified change of physical parameters of the model of the investigated mechanical system was first described. Then, an alternative approach based on computational information entropy was presented and evaluated. This alternative approach allowed to perform successful fault diagnosis. The whole problem was demonstrated on a very simple example of a one-mass system.

These results can be interpreted by the hypothesis: the quality of the measured signals does not allow to make a successful identification of the model of the investigated mechanical system. However, the information content in the measured signals is sufficient to detect this change, i.e., the information about the change in the mechanical system is strong enough for fault diagnosis.

This hypothesis will be further investigated and validated in future research. The current study is performed on a simple system; application to a more complex structure would require more data to properly evaluate the state of the system.

## 6. Acknowledgement

This paper was created with the support of the project TN02000010 of National Competence Centre of Mechatronics and Smart Technologies for Mechanical Engineering cofounded by the Technology Agency of the Czech Republic, within the National Centres of Competence Programme.

## References

[1] Azimi, M.; Eslamlou, A. and Pekcan G. (2020). Data-Driven Structural Health Monitoring and Damage Detection through Deep Learning: State-of-the-Art Review, Sensors, Vol. 20, p. 2778, 10.1002/stc.3100.
[2] Farshidi, R.; Trieu, D.; Park, S. & Freiheit, T. (2010). Non-contact experimental modal analysis using air excitation and a microphone array, Measurement, Vol. 43, No. 6, pp. 755-765, 10.1016/j.measurement.2010.02.004.
[3] Khiem, N. & Toan, L. (2014). A novel method for crack detection in beam-like structures by measurements of natural frequencies, Journal of Sound and Vibration, Vol. 333, No. 18, pp. 4084-4103, 10.1016/j.jsv.2014.04.031.
[4] Sayyad, F. B. & Kumar, B. (2012). Identification of crack location and crack size in a simply supported beam by measurement of natural frequencies, Journal of Vibration and Control, Vol. 18, No. 2, pp. 183-190, 10.1177/1077546310395979.
[5] Li, T.; Hou, R.; Zheng, K.; Zhang, Z. & Liu, B. (2024). Automated method for structural modal identification based on multivariate variational mode decomposition and its applications in damage characteristics of subway tunnels, Engineering Failure Analysis, Vol. 163, p. 108499, 10.1016/j.engfailanal.2024.108499.
[6] Salawu, O. (1997). Detection of structural damage through changes in frequency: a review, Engineering Structures, Vol. 19, No. 9, pp. 718-723, 10.1016/S0141-0296(96)00149-6.
[7] Mehrian, S. Z.; Amrei, S. R.; Maniat, M. & Nowruzpour, S. (2016). Structural health monitoring using optimising algorithms based on flexibility matrix approach and combination of natural frequencies and mode shapes, International Journal of Structural Engineering, Vol. 7, No. 4, p. 398, 10.1504/IJSTRUCTE.2016.079287.

[8] Kim, J.-T.; Ryu, Y.-S.; Cho, H.-M. & Stubbs, N. (2003). Damage identification in beam-type structures: frequency-based method vs mode-shape-based method, Engineering Structures, Vol. 25, No. 1, pp. 57-67, 10.1016/S0141-0296(02)00118-9.

[9] Silva, M.; Santos, A.; Santos, R.; Figueiredo, E.; Sales, C. & Costa, J. C. (2019). Deep principal component analysis: An enhanced approach for structural damage identification, Structural Health Monitoring, Vol. 18, No. 5-6, pp. 1444-1463, 10.1177/1475921718799070.

[10] Shadan, F.; Khoshnoudian, F. & Esfandiari, A. (2016). A frequency response-based structural damage identification using model updating method, Structural Control and Health Monitoring, Vol. 23, No. 2, pp. 286-302, 10.1002/stc.1768.

[11] Bandara, R. P.; Chan, T. H. & Thambiratnam, D. P. (2014). Frequency response function based damage identification using principal component analysis and pattern recognition technique, Engineering Structures, Vol. 66, pp. 116-128, 10.1016/j.engstruct.2014.01.044.

[12] Homaei, F.; Shojaee, S. & Ghodrati Amiri, G. (2016). Multiple-structural damage detection using measured frequency response function, Iranian Journal of Structural Engineering, Vol. 2, No. 1, pp. 13-18.

[13] Padil, K. H.; Bakhary, N.; Abdulkareem, M.; Li, J. & Hao, H. (2020). Non-probabilistic method to consider uncertainties in frequency response function for vibration-based damage detection using Artificial Neural Network, Journal of Sound and Vibration, Vol. 467, p. 115069, 10.1016/j.jsv.2019.115069.

[14] Bandara, R. P.; Chan, T. H. & Thambiratnam, D. P. (2014). Structural damage detection method using frequency response functions, Structural Health Monitoring, Vol. 13, No. 4, pp. 418-429, 10.1177/1475921714522847.

[15] Nguyen, V. D. & Nguyen, N. T. (2015). A Method for Improving the Quality of Collective Knowledge, Proceedings of 7th Asian Conference on Intelligent Information and Database Systems 2015, Bali, Indonesia, March 23–25, pp. 75-84, 10.1007/978-3-319-15702-3_8.

[16] Steinbauer, P.; Neusser, Z.; Bukovsky, I. & Neruda, M. (2019). Lighting Pole Health Monitoring for Predictive Maintenance," Procedia Structural Integrity, Vol. 17, pp. 799-805, 10.1016/j.prostr.2019.08.106.

[17] Dackermann, U.; Smith, W. A.; Alamdari, M. M. & Randall, R. B. (2019). Cepstrum-based damage identification in structures with progressive damage, Structural Health Monitoring, Vol. 18, No. 1, pp. 87-102, 10.1177/1475921718804730.

[18] Dackermann, U.; Smith, W. A. & Randall, R. B. (2014). Damage identification based on response-only measurements using cepstrum analysis and artificial neural networks, Structural Health Monitoring, Vol. 13, No. 4, pp. 430-444, 10.1177/1475921714542890.

[19] Bukovsky, I.; Kinsner, W.; Maly, V. & Krehlik, K. (2011). Multiscale Analysis of False Neighbors for state space reconstruction of complicated systems, 2011 IEEE Workshop On Merging Fields Of Computational Intelligence And Sensor Technology, pp. 65-72, 10.1109/MFCIST.2011.5949517.

[20] Bukovsky, I.; Kinsner, W. & Homma, N. (2019). Learning Entropy as a Learning-Based Information Concept, Entropy, Vol. 21, No. 2, p. 166, 10.3390/e21020166.

[21] Jamin, A. & Humeau-Heurtier, A. (2019). (Multiscale) Cross-Entropy Methods: A Review, Entropy, Vol. 22, No. 1, p. 45, 10.3390/e22010045.

[22] Kumar, A.; Gandhi, C.; Zhou, Y.; Tang, H. & Xiang, J. (2020). Fault diagnosis of rolling element bearing based on symmetric cross entropy of neutrosophic sets, Measurement, Vol. 152, p. 107318, 10.1016/j.measurement.2019.107318.

[23] Chauhan, S.; Singh, M. & Kumar Aggarwal, A. (2021). An effective health indicator for bearing using corrected conditional entropy through diversity-driven multi-parent evolutionary algorithm," Structural Health Monitoring, vol. 20, no. 5, pp. 2525-2539, 9 2021, 10.1177/1475921720962419.

[24] Chauhan, S.; Vashishtha, G.; Kumar, R.; Zimroz, R.; Gupta, M. K. & Kundu, P. (2024). An adaptive feature mode decomposition based on a novel health indicator for bearing fault diagnosis, Measurement, Vol. 226, p. 114191, 10.1016/j.measurement.2024.114191.

[25] Lin, T.-K. & Liang, J.-C. (2015). Application of multi-scale (cross-) sample entropy for structural health monitoring, Smart Materials and Structures, Vol. 24, No. 8, p. 085003, 10.1088/0964-1726/24/8/085003.

[26] Lin, T.-K. & Chien, Y.-H. (2019). Performance Evaluation of an Entropy-Based Structural Health Monitoring System Utilizing Composite Multiscale Cross-Sample Entropy, Entropy, Vol. 21, No. 1, p. 41, 10.3390/e21010041.

[27] Bekker, J. (2013). Multi-Objective Buffer Space Allocation with the Cross-Entropy Method, International Journal of Simulation Modelling, Vol. 12, No. 1, pp. 50-61, 10.2507/IJSIMM12(1)5.228.

[28] Gallimard, L. (2019). Adaptive reduced basis strategy for rare-event simulations, International Journal for Numerical Methods in Engineering, Vol. 120, No. 3, pp. 283-302, 10.1002/nme.6135.

[29] Motwani, A.; Shukla, P. K. & Pawar, M. (2023). Novel framework based on deep learning and cloud analytics for smart patient monitoring and recommendation (SPMR), Journal of Ambient Intelligence and Humanized Computing, Vol. 14, No. 5, pp. 5565-5580, 10.1007/s12652-020-02790-6.