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COMPARATIVE ASSESSMENT OF DATA NORMALIZATION METHODS FOR MODAL-BASED SHM

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Abstract. Accurate identification and assessment of damage in civil structures are crucial for ensuring structural integrity and public safety. Damage detection is one of the main aims of modal-based Structural Health Monitoring (SHM), which implies observing damage-sensitive features, such as natural frequencies, over time. However, those are typically sensitive not only to structural damage but also to environmental and operational variables (EOVs), such as humidity, operational loading, wind, and temperature. EOVs can cause changes in natural frequencies similar to those caused by actual damage, thus jeopardizing the reliability of automated damage detection by SHM systems. To address this challenge, several data normalization methods to be applied in the context of modal-based SHM have been proposed. These methods aim to mitigate the EOV effects, thereby allowing for more accurate and reliable damage identification. This research presents a comparative study of different methods: Multiple Linear Regression (MLR), linear Principal Component Analysis (PCA), and Kernel Principal Component Analysis (KPCA), evaluating their effectiveness using real-case data from the Z24 Bridge benchmark. Within the challenging context of the Z24 bridge, where EOVs induced a nonlinear behavior, the potential benefits of incorporating complementary techniques, such as clustering, to augment the efficacy of traditional methods are discussed.

1 INTRODUCTION

Over time, civil engineering structures are susceptible to processes of aging, environmental degradation, and fatigue. Moreover, they are vulnerable to the damage triggered by earthquakes, fires, or explosions. These factors collectively contribute to the potential deterioration of structures, ultimately affecting their safety. Thus, the accurate identification and assessment of damage in civil structures are crucial for ensuring structural integrity and public safety.

Damage detection is one of the main aims of modal-based Structural Health Monitoring

(SHM), which implies analyzing damage-sensitive features, such as modal properties (natural frequencies, damping ratios, and mode shapes), over time. The basis of this approach is that damage-induced changes in structural properties lead to observable changes in modal properties [1,2]. Vibration-based damage detection methods fall into two categories: model-based and data-driven methods. The former use numerical models, such as Finite Element models, and compare predicted and actual structural behavior to detect damage [3]. The latter, on the other hand, analyze the collected data without strong structural assumptions, looking for anomalous patterns to identify damage. In SHM, data-driven methods are gaining attention due to their low-complexity requirements, resilience to structural changes, and reduced computational efforts.

Data-driven damage detection commonly relies on eigenfrequencies as damage-sensitive features [4]. However, those are sensitive not only to structural damage but also to environmental and operational variables (EOVs), such as humidity, loading, wind, and temperature [5]. The influence of EOVs often matches or even surpasses that of actual damage [2,6]. For this reason, the reliability of modal-based SHM systems is often jeopardized.

Data normalization for damage-sensitive features aims to differentiate between damage-induced changes and those stemming from EOVs. This involves creating models from data collected under healthy structural conditions to establish a baseline for understanding how EOVs affect the dynamic behavior. However, this represents a challenging task in SHM. Over the last few decades, several data normalization methods have been proposed [5,7] mainly falling into two categories based on whether environmental data are directly measured (input-output methods) or not (output-only methods). Input-output methods analyze the relationship between EOVs (inputs) and structural responses (outputs) to predict and separate EOV-induced variations from the structural response. Regression analysis (RA) belongs to this class of methods [4]. Output-only methods rely on creating a black-box model of the structure using suitable output data acquired during exposure to EOVs. Some examples include principal component analysis (PCA) [8], factor analysis (FA) [9], second-order blind identification (SOBI) [10], and cointegration analysis (CA) [11]. To date, because of the attention this issue has garnered, significant research efforts have been spent to develop robust models using advanced approaches [10-15].

Despite the extensive research conducted on data normalization techniques, most of these studies have primarily focused on the development of new methods. Only a limited number of studies have focused on the comparative performance assessment of different methods [16,17]. This study evaluates different data normalization models using real-case data from the Z24 Bridge benchmark [18]. The paper first illustrates the theoretical background of the examined normalization models. The obtained results are comparatively discussed afterwards, also exploring the potential benefits of incorporating complementary techniques, such as clustering, to augment the efficacy of traditional methods. This extensive evaluation aims to provide valuable insights into the selection of data normalization approaches in SHM applications.

3 DATA NORMALIZATION AND NOVELTY ANALYSIS

Detecting anomalies or novel patterns in a structure's dynamic behavior requires comparing the predictions of trained models, built from data associated with the healthy state of the monitored structure, and newly collected data. The core purpose of such a model is to capture the EOV-induced variations in the selected feature, isolating only the damage-sensitive part. The above is often formulated through the error matrix $\mathbf{E} \in \mathbb{R}^{n \times N}$ which contains the residues in the data associated with the novel patterns. The Euclidean norm of the vector $\mathbf{E}_k$ is calculated to estimate the overall error at a given time instant t_k.

$$\|\mathbf{E}_k\| = \|\mathbf{Y}_{ky} - \widehat{\mathbf{Y}}_{ky}\| \tag{1}$$

In this context, we have the observation matrix $\mathbf{Y} \in \mathbb{R}^{n \times N}$, containing N-length time histories of n selected damage-sensitive features. On the other hand, $\widehat{\mathbf{Y}} \in \mathbb{R}^{n \times N}$ represents the model predictions, constituting a central focus within novelty analysis. To address this, four different methods are applied in the context of the present paper for comparative assessment purposes.

3.2 Multiple Linear Regression

One of the most straightforward approaches to establish a relationship between damage-sensitive features and EOVs is through the Multiple Linear Regression (MLR) method. This method is typically categorized as an input-output technique, making it suitable when comprehensive input data (EOV measurements) are available. In mathematical terms, the relationship between damage features and EOVs is expressed as follows:

$$\widehat{\mathbf{Y}} = \boldsymbol{\beta}\mathbf{Z} \tag{2}$$

where $\widehat{Y}_i \in \mathbb{R}^{1 \times n}$ represents the estimated values for the i-th instance ($i = 1, 2, \ldots, t$) of the damage-sensitive features, $\beta_j \in \mathbb{R}^{1 \times (p+1)}$ holds the j-th set of MLR coefficients, and $Z_i \in \mathbb{R}^{1 \times (p+1)}$ holds the corresponding values of the EOVs, often referred to as predictors. Estimating the $\boldsymbol{\beta}$ coefficients commonly employ the Least-Square Method (LSM).

3.2 Principal Component Analysis

In case obtaining EOV measurements is challenging, adopting only-output methods becomes a practical approach. These methodologies prove highly effective in extracting valuable insights from the available structural response data, disregarding the input data consideration. Principal Component Analysis (PCA) is a statistical method used for dimensionality reduction, transforming a dataset into a lower-dimensional space while keeping the utmost variability within the data. The initial Principal Component (PC) accounts for the highest amount of variation, with each subsequent component accounting for a progressively lesser degree of variation [8]. The PCA method aims to project the original data $\mathbf{Y}$ in the PC space and then remap back to the original space ($\widehat{\mathbf{Y}}$) by retaining only the subset of the largest PCs as follows:

$$\mathbf{Y} = \mathbf{P}^{\mathrm{T}}\mathbf{Z} \tag{3}$$

$$\widehat{\mathbf{Y}} = \widehat{\mathbf{P}}^{\mathrm{T}}\widehat{\mathbf{P}}\mathbf{Y} \tag{4}$$

where the transformation matrix, $\mathbf{P} \in \mathbb{R}^{N \times n_t}$, contains the singular vectors of the covariance matrix of $\mathbf{Y}$, $\mathbf{Z} \in \mathbb{R}^{N \times (p+1)}$ is a matrix with the projections of $\mathbf{Y}$ in the PC space. By retaining the first n_u columns of $\mathbf{P}$, a rectangular reduced transformation matrix $\widehat{\mathbf{P}} \in \mathbb{R}^{N \times n_u}$ is obtained. Defining n_u in PCA is crucial, striking a balance between accounting EOV-induced variability (sufficient size) and enhancing anomaly detection sensitivity (sufficiently small). A common criterion involves retaining a given percentage of the total variance [2].

3.1 Kernel Principal Component Analysis

Real structures often exhibit complex and nonlinear dynamic behavior. These nonlinearities can pose challenges for traditional linear normalization techniques, which may struggle to capture such complexities effectively. Thus, kernel-based approaches have been proposed for handling data with nonlinear relationships. They involve embedding the data ($\mathbf{Y}_k$) into a higher-dimensional feature space ($\mathbf{\Phi}(\mathbf{Y}_k)$), where patterns can be more effectively identified as linear relationships. In the case of Kernel Principal Component Analysis (KPCA), PCA is applied within a feature space defined by a kernel through the dual representation.

In KPCA the damage-sensitive feature vector ($\mathbf{Y}_{\boldsymbol{k}}$) is mapped into a higher-dimensional feature space through a nonlinear embedding mapping ($\mathbf{\Phi}(\cdot)$); the model (Eq. 5) is defined in terms of the EOV sequences ($\mathbf{u}_k$) and the misfit between data and model predictions ($\hat{\mathbf{e}}_k$).

$$\mathbf{\Phi}(\mathbf{Y}_{\boldsymbol{k}}) = \mathbf{H_0}\mathbf{u}_{\boldsymbol{k}} + \tilde{\mathbf{e}}_{\boldsymbol{k}} \tag{5}$$

$$\tilde{\mathbf{e}}_{\boldsymbol{k}} = \mathbf{\Phi}(\mathbf{Y}_{\boldsymbol{k}}) - \mathbf{H_0}\mathbf{u}_{\boldsymbol{k}} = \mathbf{\Phi}(\mathbf{Y}_{\boldsymbol{k}}) - \mathbf{\Phi}(\hat{\mathbf{Y}}_{\boldsymbol{k}}) \tag{6}$$

Identifying patterns within a feature space without explicit computation of the mapping function is enabled by a kernel function (κ) as per Mercer's theorem, which stands that any positive semi-definite symmetric kernel function can be represented as an inner product in a high-dimensional feature space, resulting in a linear transformation (dual representation), Eq. 7.

$$\mathbf{K}_{ij} = \kappa(\mathbf{Y}_i, \mathbf{Y}_j) = \langle \phi(\mathbf{Y}_i), \phi^{\mathrm{T}}(\mathbf{Y}_j) \rangle, \quad \phi: x \mapsto \phi(x) \in F, \text{for } i,j = 1, \dots, \ell \tag{7}$$

The dual representation method, facilitated by the kernel, allows for the estimation of covariance relationships between $\phi(\mathbf{Y}_i)$ and $\phi(\mathbf{Y}_j)$ in the high-dimensional feature space, allowing PC computation. Separating the eigenvectors $\mathbf{U}_1 \in \mathbb{R}^{n_t \times n_u}$ associated with the n_u largest eigenvalues ($\mathbf{\Sigma}_1 \in \mathbb{R}^{n_u}$), and the remaining ones $\mathbf{U}_2 \in \mathbb{R}^{n_t \times (n_s - n_u)}$ with the corresponding eigenvalues ($\mathbf{\Sigma}_2 \in \mathbb{R}^{n_s - n_u}$), the error term can be computed as follows:

$$\|\tilde{\mathbf{e}}_k\| = \mathbf{\Phi}^T(\mathbf{Y}_{\boldsymbol{k}})\tilde{\mathbf{\Phi}}\mathbf{U_2}\mathbf{U}_2^T\tilde{\mathbf{\Phi}}^T\mathbf{\Phi}(\mathbf{Y}_{\boldsymbol{k}}) \tag{8}$$

and it is uncorrelated with the unknown EOVs. The Gaussian or Radial Basis Function (RBF) kernel (Eq. 9) is often employed in the context of SHM applications [14]. The parameter σ controls the bandwidth of the inner product matrix **K**.

$$k(\mathbf{Y}_i, \mathbf{Y}_j) = \exp\left(-\frac{\|\mathbf{Y}_i - \mathbf{Y}_j\|^2}{2\sigma^2}\right) \tag{9}$$

The kernel width (σ) and the number of extracted PCs (n_u) are crucial parameters in KPCA. Some authors have suggested maximizing the information entropy of the inner product **K** (I_{ent}) to obtain the optimal σ value [14].

3.2 Local PCA using Gaussian Mixture Model

In the last decades, some authors have introduced clustering techniques with anomaly score functions for damage detection. Yan [8] proposed a PCA-based damage detection method under varying environmental conditions, involving a two-step procedure: data clustering and Local PCA (L-PCA) analysis. This approach captures the nonlinear behavior of vibration features attributed to EOVs by applying L-PCA separately to each subregion. Subsequently, they identified structural damage by analyzing the residual error of the reconstructed data.

In this study the Gaussian Mixture Model (GMM) is adopted as a clustering method. It relies on the assumption that the underlying data distribution is a mixture of multiple Gaussian distributions. It provides a probabilistic framework for clustering, where each data point is associated with a probability of belonging to each cluster. A Gaussian Mixture is a function composed of several Gaussian distributions, each identified by $k \in \{1, \dots, K\}$, where K is the number of clusters of the dataset. Each Gaussian k in the mixture is defined in terms of its parameters μ, Σ and π, where μ is the mean, Σ is the covariance, and π is the mixing probability.

$$p(z_k = 1|x_n) = \frac{p(\mathrm{x}_n|z_k = 1)p(z_k = 1)}{\sum_{j=1}^{K} p(\mathrm{x}_n|z_j = 1)p(z_j = 1)} = \frac{\pi_k \mathcal{N}(x_n|\mu_k, \Sigma_\mathrm{k})}{\sum_{j=1}^{K} \pi_j \mathcal{N}\left(x_n|\mu_j, \Sigma_\mathrm{j}\right)} = \gamma(z_{nk}) \tag{10}$$

The GMM clustering algorithm iteratively estimates the parameters using the Expectation-Maximization (EM) algorithm. In the generic EM step, the algorithm calculates the probability of each data point belonging to each cluster based on the current parameter estimates. The GMM algorithm continues these iterations until convergence, where the parameter estimates $\theta = \{\pi, \mu, \Sigma\}$ stabilize.

4 CASE STUDY

The Z24 Bridge benchmark is a unique dataset of long-term (nearly a year, from November 11, 1997, to September 11, 1998) continuous monitoring of the dynamic behavior of a full-scale structure and the associated environmental and operational conditions. A detailed description of the bridge can be found in [18]. Towards the end of the monitoring period, controlled gradual damage was induced on the structure, allowing to assess whether realistic damage had a measurable influence on bridge dynamics. Collectively, these factors contributed to the significance of the Z24 Bridge as a benchmark, enabling researchers to gain valuable knowledge about the structural behavior and performance under realistic conditions.

Eigenfrequencies are a frequent choice as damage-sensitive features owing to their inherent sensitivity to structural damage, ease of acquisition, and extensive validation for damage detection. For these reasons, the identified frequencies of the Z-24 bridge were selected as damage-sensitive features in this study. Modal identification carried out by Peeters and De Roeck [4] resulted in four modes with sufficient accuracy. The reported differences in the identified frequencies (14-18%) in the healthy state is assumed to be related to EOVs [4].

The duration of the training stage is a critical parameter in modeling, and it is typically set at one year, which is recognized as sufficient for effectively capturing variations induced by EOVs [2]. However, the Z24 bridge benchmark reported that the first damage occurred on August 05, 1998. Thus, the data recorded before this date was regarded as the healthy state of the structure. For model training purposes, the first 3000 data points, comprising roughly 50% of the available data (6 months), were utilized.

It is noteworthy that nonnumeric values were identified within the dataset, thus prompting the need for cleaning or preprocessing. Reynders et al. [14] used linear interpolation between the boundary values of non-numeric data to complete the missing information; herein, a similar approach was adopted.

5 RESULTS AND DISCUSSION

5.1 MLR

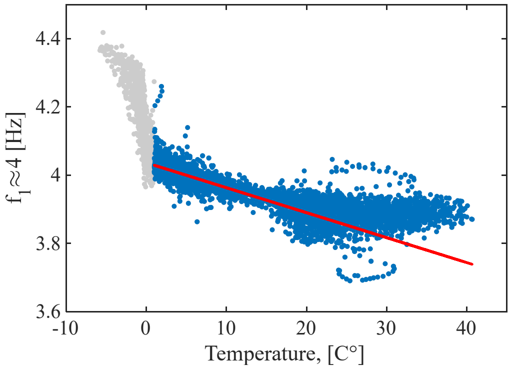
Analyzing the correlation between the identified frequencies and the temperature of the pavement exhibits a bilinear behavior around 0°C (Fig. 1a). To maintain the assumption of linearity within the MLR model, only data associated with temperatures above 0°C was considered, minimizing any potential bias.

In this study, the relationship between a single dependent variable (pavement temperature) and a set of independent variables, represented by identified natural frequencies, has been established. The obtained regression model coefficients are shown in Table 1, and the results of the overall error of the predicted model are shown in Fig. 1(b).

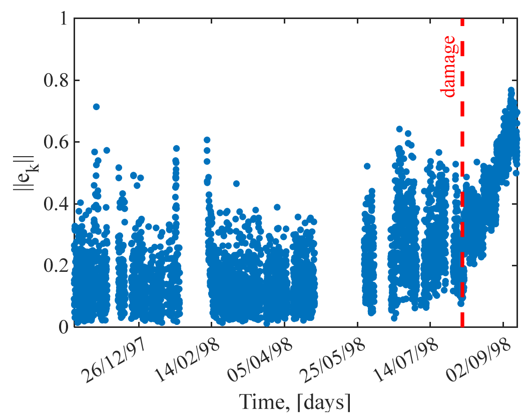
Table 1: MLR model coefficients.

β	f_1	f_2	f_3	f_4
1	4.1290	5.3031	10.4580	11.1561
2	-0.0226	-0.0205	-0.0547	-0.0580

The MLR model shows poor performance in reproducing the variance induced by EOVs (Fig. 1b). Results associated with the training stage (blue dots) as well as test data indicate a noticeable influence of EOVs, making it difficult to distinguish between the damaged (yellow crosses) and undamaged (orange triangles) states. This may suggest that the measured temperature is not representative of the temperature field in the structure, thus introducing bias in the MLR model.



(a)

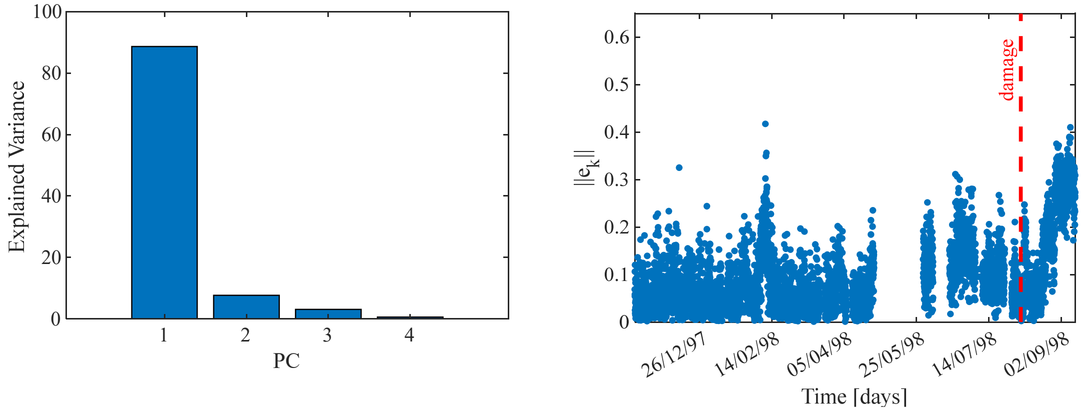


(b)

Figure 1: (a) The region of the dataset exhibiting approximate linearity and (b) overall MLR model misfit.

5.2 PCA

In the application of PCA to set the model of environmental variability of natural frequencies, the first two principal components, which roughly seize 97% of the total variance, were considered. As shown in Fig. 2, the model falls short in fully mitigating the impact of environmental factors. This was expected because PCA is designed for linear data analysis. This shortfall is exhibited in the undamaged stage, where the influence of EOV-induced variance is noticeable.



(a) (b)

Figure 2: PCA: (a) explained variance and (b) overall model misfit.

5.3 KPCA

In KPCA, the initial step involves determining the optimal value for the hyperparameter σ of the kernel function. This is obtained in agreement with the procedure outlined in [14]. After setting the optimal hyperparameter σ to the optimal value (0.405, which is consistent with the findings reported in [14]), PCA is carried out in the kernel space after data centering [14]. The error between the KPCA model predictions and the measured data is shown in Fig. 3.

The KPCA method exhibits higher effectiveness to capture and compensate for EOV influence compared to linear methods (Fig. 3), allowing to effectively distinguish between the damaged and undamaged states.

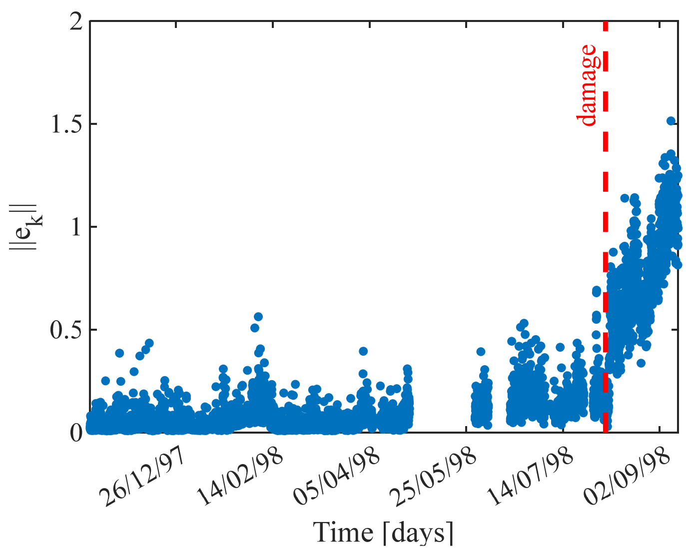


Figure 3: KPCA model misfit.

5.4 LPCA-GMM

The Local PCA method requires definition of both the number of clusters and the number of principal components to retain in each cluster. In this application we used GMM clustering on the training dataset with three distinct clusters based on the relationship between f_1 and f_2 (Figure 6a). It is worth mentioning that the choice of feature pairs for data clustering may result in different clusters. Subsequently, PCA was applied to each cluster, projecting it onto the entire dataset to obtain the misfit for each. A minimum distance criterion is then applied to compute the overall error of the model.

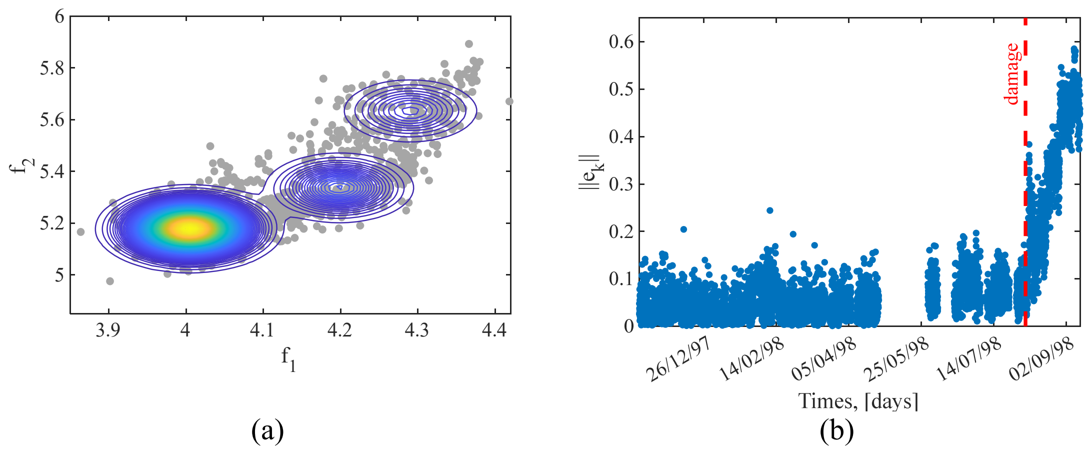


Figure 4: LPCA-GMM model results: (a) resulting clusters, (b) overall model misfit.

The application of clustering techniques effectively mitigates the inherent limitations of the PCA method when applied to nonlinear problems (Fig. 4b). This leads to a significantly improved capacity for compensating EOV-induced effects, surpassing the performance of conventional PCA. The comparison of the normalized overall model misfit of KPCA and LPCA-GMM shows a remarkable similarity (Fig. 5). However, during the training phase, KPCA exhibits better performance. This outcome was expected, as the kernel deals with nonlinearity, while LPCA-GMM seeks to approximate the transformation of nonlinear problems into linear ones by segmenting the dataset into subsets.

4 CONCLUSIONS

In this paper, four different normalization techniques, including MLR, PCA, KPCA and LPCA-GMM, were evaluated to comparatively assess their effectiveness in the compensation of EOV-induced effects. These methods were applied to the dataset of the Z24 Bridge benchmark. Among the considered normalization methods, LPCA is a widely known technique that often employs clustering based on Euclidean distances or similar metrics. However, in this paper, the utilization of GMM was attempted, obtaining satisfactory results.

As expected, the linear methods (MLR and PCA) poorly perform due to the nonlinearity of the dataset, reducing their practical usefulness to compensate for EOVs efficiently. KPCA exhibits higher efficiency compared to traditional linear methods. This is attributable to the leveraging of the kernel approach to capture the non-linear behavior by mapping data into higher-dimensional spaces where linear separability is achieved.

Despite LPCA-GMM achieved a similar result to KPCA, meaning that mixing clustering techniques with linear methods may improve their performance, KPCA model can still be considered more effective in removing the EOV-induced effects because the performance of LPCA-GMM heavily depends on the choice of the feature pair for data clustering. On the other hand, the computational efforts associated with KPCA are relatively higher than for the other evaluated methods. This may raise difficulties in applying KPCA in complex cases with extensive data processing requirements.

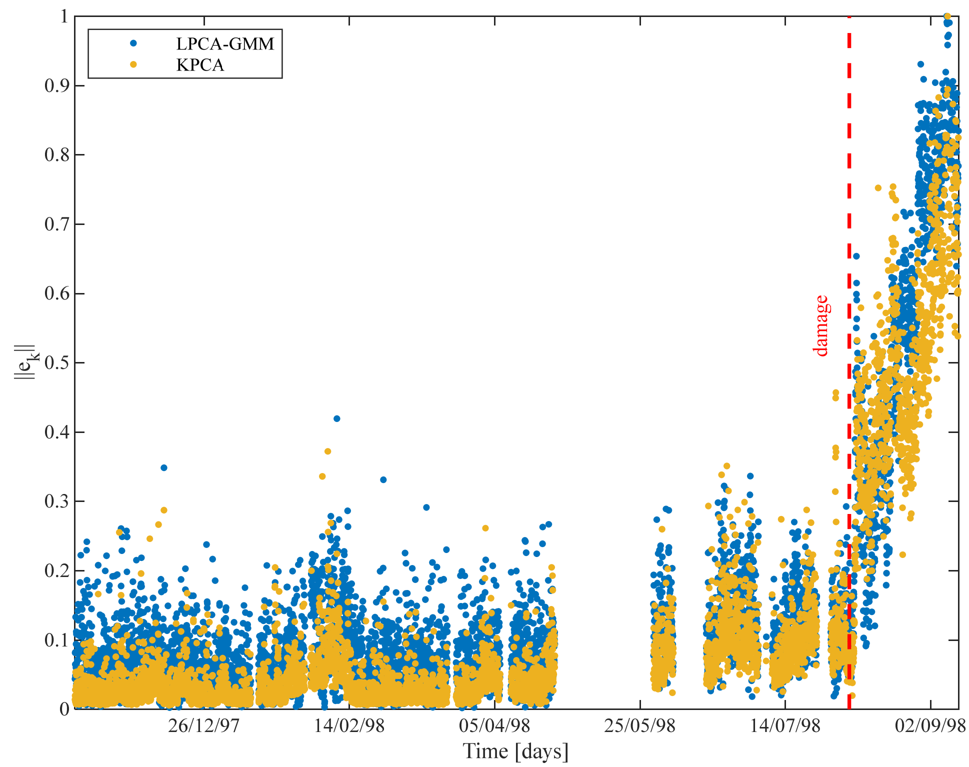


Figure 5: Comparisons between the misfits obtained by LPCA-GMM and KPCA.

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REFERENCES

[1] W. Fan, P. Qiao, Vibration-based Damage Identification Methods: A Review and Comparative Study, Struct. Heal. Monit. 10 (2010) 83–111. https://doi.org/10.1177/1475921710365419.

[2] C. Rainieri, Environmental Influence on Modal Parameters: Linear and Nonlinear Methods for Its Compensation in the Context of Structural Health Monitoring, in: A. Cury, D. Ribeiro, F. Ubertini, M.D. Todd (Eds.), Struct. Heal. Monit. Based Data Sci. Tech., Springer International Publishing, Cham, 2022: pp. 269–288. https://doi.org/10.1007/978-3-030-81716-9_13.

[3] C.R. Farrar, K. Worden, Structural Health Monitoring: A Machine Learning Perspective, 2012. https://doi.org/https://doi.org/10.1002/9781118443118.ch1.

[4] B. Peeters, G. De Roeck, One-year monitoring of the Z24-Bridge: environmental effects versus damage events, Earthq. Eng. Struct. Dyn. 30 (2001) 149–171. https://doi.org/https://doi.org/10.1002/1096-9845(200102)30:2<149::AID-EQE1>3.0.CO;2-Z.

[5] H. Sohn, Effects of environmental and operational variability on structural health monitoring, Philos. Trans. R. Soc. A Math. Phys. Eng. Sci. 365 (2007) 539–560. https://doi.org/10.1098/rsta.2006.1935.

[6] Z. Wang, D.-H. Yang, T.-H. Yi, G.-H. Zhang, J.-G. Han, Eliminating environmental and operational effects on structural modal frequency: A comprehensive review, Struct. Control Heal. Monit. 29 (2022) e3073. https://doi.org/https://doi.org/10.1002/stc.3073.

[7] Q. Han, Q. Ma, J. Xu, M. Liu, Structural health monitoring research under varying temperature condition: a review, J. Civ. Struct. Heal. Monit. 11 (2021) 149–173. https://doi.org/10.1007/s13349-020-00444-x.

[8] A.-M. Yan, G. Kerschen, P. De Boe, J.-C. Golinval, Structural damage diagnosis under varying environmental conditions—part II: local PCA for non-linear cases, Mech. Syst. Signal Process. 19 (2005) 865–880. https://doi.org/https://doi.org/10.1016/j.ymssp.2004.12.003.

[9] A. Deraemaeker, E. Reynders, G. De Roeck, J. Kullaa, Vibration-based structural health monitoring using output-only measurements under changing environment, Mech. Syst. Signal Process. 22 (2008) 34–56. https://doi.org/https://doi.org/10.1016/j.ymssp.2007.07.004.

[10] C. Rainieri, F. Magalhaes, D. Gargaro, G. Fabbrocino, A. Cunha, Predicting the variability of natural frequencies and its causes by Second-Order Blind Identification, Struct. Heal. Monit. 18 (2018) 486–507. https://doi.org/10.1177/1475921718758629.

[11] J. Huang, D. Li, H. Li, A new regime-switching cointegration method for structural health monitoring under changing environmental and operational conditions, Measurement. 212 (2023) 112682. https://doi.org/https://doi.org/10.1016/j.measurement.2023.112682.

[12] Z.H. F., N.Y. Q., K.J. M., Eliminating Temperature Effect in Vibration-Based Structural Damage Detection, J. Eng. Mech. 137 (2011) 785–796. https://doi.org/10.1061/(ASCE)EM.1943-7889.0000273.

[13] A. Kita, N. Cavalagli, F. Ubertini, Temperature effects on static and dynamic behavior of Consoli Palace in Gubbio, Italy, Mech. Syst. Signal Process. 120 (2019) 180–202.

https://doi.org/https://doi.org/10.1016/j.ymssp.2018.10.021.

[14] E. Reynders, G. Wursten, G. De Roeck, Output-only structural health monitoring in changing environmental conditions by means of nonlinear system identification, Struct. Heal. Monit. 13 (2013) 82–93. https://doi.org/10.1177/1475921713502836.

[15] H. Shi, K. Worden, E.J. Cross, A regime-switching cointegration approach for removing environmental and operational variations in structural health monitoring, Mech. Syst. Signal Process. 103 (2018) 381–397. https://doi.org/https://doi.org/10.1016/j.ymssp.2017.10.013.

[16] G. Comanducci, F. Magalhães, F. Ubertini, Á. Cunha, On vibration-based damage detection by multivariate statistical techniques: Application to a long-span arch bridge, Struct. Heal. Monit. 15 (2016) 505–524. https://doi.org/10.1177/1475921716650630.

[17] D. García Cava, L.D. Avendaño-Valencia, A. Movsessian, C. Roberts, D. Tcherniak, On Explicit and Implicit Procedures to Mitigate Environmental and Operational Variabilities in Data-Driven Structural Health Monitoring BT - Structural Health Monitoring Based on Data Science Techniques, in: A. Cury, D. Ribeiro, F. Ubertini, M.D. Todd (Eds.), Springer International Publishing, Cham, 2022: pp. 309–330. https://doi.org/10.1007/978-3-030-81716-9_15.

[18] E. Reynders, G. De Roeck, Continuous Vibration Monitoring and Progressive Damage Testing on the Z24 Bridge, in: Encycl. Struct. Heal. Monit., 2009. https://doi.org/https://doi.org/10.1002/9780470061626.shm165.