

Lāsma Ratnika

**ADAPTIVE SEGMENTED REGRESSION METHOD
FOR REDUCING THE IMPACT OF ENVIRONMENTAL
FACTORS ON DYNAMIC PARAMETERS IN LONG-TERM
STRUCTURAL HEALTH MONITORING DATA**

Summary of the Doctoral Thesis



RIGA TECHNICAL UNIVERSITY

Faculty of Civil and Mechanical Engineering

Institute of Structural Engineering

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**ADAPTIVE SEGMENTED REGRESSION
METHOD FOR REDUCING THE IMPACT
OF ENVIRONMENTAL FACTORS ON DYNAMIC
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RIMS JANĒLIUKŠTIS

RTU Press

Riga, 2026

Ratnika, L. Adaptive Segmented Regression Method for Reducing the Impact of Environmental Factors on Dynamic Parameters in Long-Term Structural Health Monitoring Data. Summary of the Doctoral Thesis. Riga: RTU Press, 2026. 66 p.

Published in accordance with the decision of the Promotion Council “RTU P-06”, Minutes No. 04030-9.6/8.

This research has been supported by:

- Riga Technical University’s Doctoral Grant programme 2021–2023;
- European Social Fund within the Project No. 8.2.2.0/20/I/008 “Strengthening of PhD students and academic personnel of Riga Technical University and BA School of Business and Finance in the strategic fields of specialisation” of the Specific Objective 8.2.2 “To Strengthen Academic Staff of Higher Education Institutions in Strategic Specialisation Areas” of the Operational Programme “Growth and Employment”.



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Cover image from www.shutterstock.com

<https://doi.org/10.7250/9789934373497>

ISBN 978-9934-37-349-7 (pdf)

DOCTORAL THESIS PROPOSED TO RIGA TECHNICAL UNIVERSITY FOR PROMOTION TO THE SCIENTIFIC DEGREE OF DOCTOR OF SCIENCE

To be granted the scientific degree of Doctor of Science (PhD), the present Doctoral Thesis has been submitted for defence at the open meeting of the RTU Promotion Council on 9 October 2026, at 14.00 at the Faculty of Civil and Mechanical Engineering of Riga Technical University, Kipsalas Street 6A, Room 453.

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DECLARATION OF ACADEMIC INTEGRITY

I hereby declare that the Doctoral Thesis submitted for review to Riga Technical University for promotion to the scientific degree of Doctor of Science (PhD) is my own. I confirm that this Doctoral Thesis has not been submitted to any other university for promotion to a scientific degree.

Lāsma Ratnika(signature)

Date:

The Doctoral Thesis has been written in Latvian. It consists of a general review of the Doctoral Thesis, four chapters, Conclusions, 74 figures, and 8 tables; the total number of pages is 127. The Bibliography contains 210 titles.

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GENERAL REVIEW OF THE DOCTORAL THESIS

Relevance of the topic

Structural health monitoring of buildings as a scientific field can be found around 1990 [1]. In recent years, the need to ensure public safety and to improve the assessment of the technical condition of structures has significantly increased interest in the development and application of instrumented monitoring systems for real buildings.

The world is currently experiencing a gradual ageing of infrastructure and building stock, which creates new challenges for the safe operation of buildings. Many buildings continue to be used well beyond their intended service life, thereby requiring periodic assessments of the technical condition of the structural elements. For example, current regulations in Latvia [2] state that building owners are required to carry out a technical inspection within a certain period, while a repeated inspection is mandatory only after 10 years. During these 10 years, the building owner is not required to carry out additional technical inspections of the structure to assess the current technical condition of the building or its individual structural elements. Based on the assessment and recommendations regarding the technical condition of the building provided by a certified structural engineer, building owners carry out the necessary repairs, and users continue to operate the building. The regulations also do not specify that the issued technical inspection reports must be reviewed or repeated under the supervision of another certified structural engineer. Theoretically, the next 10 years of the building's operation depend on the attention, experience, knowledge, and decision-making abilities of the structural engineer.

Structural health monitoring, as a periodic assessment of the technical condition of a building and its structures, would ensure human safety even during periods when there is no mandatory obligation to carry out monitoring and would periodically update information on the technical condition of the building without the need for visual inspections. In practical application, several factors have influenced the future development of structural health monitoring. The main factors are:

- high implementation costs;
- the complexity of the structural solutions of different types of structures;
- the limited amount of monitoring data on existing buildings;
- the difficulty of separating changes caused by structural damage from changes caused by environmental conditions.

Some of the factors mentioned above can be eliminated by improving equipment and obtaining monitoring data from finite element models, but the impact of environmental factors varies in each climate zone and changes seasonally, making it difficult to predict. The dynamic parameters of structures may change not only due to damage but also due to the impact of environmental conditions. If the impact of environmental factors is not considered, structural health monitoring may produce false alarms, which reduces the reliability and efficiency of the monitoring system and leads to unnecessary repair costs. However, if the impact of environmental factors on the dynamic parameters of the structure is greater than the impact of damage, there is a risk that structural damage will not be detected in time and repaired

immediately. Therefore, under variable environmental conditions, the structural health monitoring system must be able to adaptively consider the impact of environmental factors and reduce the risk of false alarms and damage detection.

The aim and objectives of the Thesis

The Doctoral Thesis aims to develop and validate an innovative adaptive method for reducing the impact of environmental factors on monitoring data, which allows compensating for the impact of changing environmental factors on the natural frequencies of structures and increases the accuracy of structural damage detection algorithms, ensuring reliable and effective long-term structural health monitoring.

The following tasks were defined to achieve the objective of the Thesis.

1. Study and summarise the existing information on methods for monitoring the technical condition of buildings and civil engineering structures, as well as to analyse the impact of environmental factors on the dynamic parameters of structures.
2. Analyse long-term monitoring experimental data for the two-storey wooden frame and the Filomena Delli Castelli bridge. To summarise data on natural frequency and the impact of environmental factors.
3. Evaluate the changes in the long-term natural frequency monitoring data under the influence of seasonally changing environmental factors. To evaluate the impact of environmental factors on the natural frequencies of building structures.
4. Develop an adaptive method for reducing the impact of environmental factors using a combined machine learning algorithm and segmented modelling of the impact of environmental factors to accurately separate changes in natural frequency values caused by the environmental factors from changes caused by structural damage.
5. Evaluate the accuracy of the structural damage detection algorithm before the application of the environmental impact reduction method by determining the impact of environmental factors on false positive and false negative classifications.
6. Apply the method for reducing the impact of environmental factors to the natural frequency data from long-term monitoring of the wooden frame and Filomena Delli Castelli bridge.
7. Evaluate the accuracy of the structural damage detection algorithm after applying the method of reducing the impact of environmental factors to the monitoring data of the wooden frame, by determining the accuracy of the algorithm to identify damaged and undamaged structural data.
8. Evaluate the effectiveness of applying the environmental impact reduction method to bridge monitoring data by analysing changes in natural frequencies.

Scientific novelty of the research

Within the framework of this research, a new adaptive method has been developed to reduce the impact of environmental factors on the natural frequencies, ensuring reliable and effective performance of structural damage detection algorithms. The method combines long-term

structural health monitoring with machine learning algorithms for data analysis, representing a significant step towards automated and accurate real-time assessment of the technical condition of building structures.

This study identified the characteristics of certain environmental factors. Analytical methods and machine learning algorithms revealed that the influence of environmental factors is nonlinear and variable over the monitoring period. The results enhance the theoretical knowledge of environmentally induced changes in natural frequencies and emphasise the importance of using nonlinear compensation models in structural health monitoring systems.

This study indicates that structural health monitoring requires an adaptive method, in which the selection of algorithms is based on the segmentation of environmental factors and the character of their impact. Comparative analysis of regression models enables the identification of the most effective model for each case, improving prediction accuracy and damage detection reliability. The composite performance metric used in the study enables the evaluation of the accuracy of each regression model. This approach provided an objective assessment of the most appropriate regression model for each environmental impact factor and each natural frequency. After correction, structural damage detection accuracy improved significantly – false positive and false negative classifications were decreased, improving the efficiency of the structural health monitoring system. In the case of bridge natural frequencies, the variance of frequency values was decreased, ensuring stable values during the monitoring period.

The method for reducing the impact of environmental factors is based on a multistep approach. This involves segmented data analysis, optimal regression model selection for each environmental segment and natural frequency, and the application of a nonlinear correction function. This approach ensures the repeatability and adaptability of the method to different types of structures and weather conditions. Correction functions are developed individually for each natural frequency, considering their different sensitivities to specific environmental factors. This approach ensures accurate compensation of environmental impacts and avoids errors that may arise from generalised corrections. The developed method is based on experimentally validated data, enabling its application to a wide range of structures.

The conclusions of the study formulate practical guidelines for the implementation of structural health monitoring in buildings. These guidelines provide a basis for implementing structural health monitoring systems in both new and existing buildings, ensuring data-driven decisions on structural condition and maintenance.

Practical application of the Doctoral Thesis

The results obtained in the study are significant for the practical implementation of structural health monitoring under variable environmental conditions, ensuring the efficiency of monitoring by compensating the impact of environmental conditions, reducing the number of false alarms, and increasing user confidence in monitoring systems. The practical applicability of the method is also reflected in optimised use of resources, as maintenance and renovation can be planned based on quantitative assessments of structural condition rather than periodic visual inspections. This promotes the transition from traditional to data-driven building

maintenance practices, which is an essential part of a sustainable construction and operation strategy. The developed method is applicable to various types of buildings and construction materials, thereby providing practical benefits to structural designers, supervisors, owners and managers of buildings who are responsible for ensuring the long-term safe operation of buildings. The method is based on available measurement devices and calculation algorithms, enabling gradual and economically justified implementation. An important advantage is the integrability of the developed method into existing structural health monitoring data. The proposed approach enables real-time association of natural frequency variations with environmental factors, ensuring automated correction and risk identification without manual data analysis. This supports the transition to data-driven building management and forms the basis for next-generation structural health monitoring and maintenance systems.

The practical significance is also reflected in the opportunity to improve regulations and guidelines regarding the inspection of buildings. The method proposed in the study can be used as a basis for recommendations on how to integrate automated structural condition monitoring into building maintenance plans.

Methodology and materials used in the research

The Doctoral Thesis employed a comprehensive research approach, combining theoretical literature analysis, experimental data processing, numerical modelling, and the application of machine learning methods for assessing the technical condition of structures. The initial stage of the study included a review of scientific literature on structural health monitoring, damage detection methods, and the impact of environmental factors on the dynamic properties of structures. The literature review identified key issues in monitoring data interpretation caused by environmental variability and assessed the limitations of existing methods for reducing the impact of environmental conditions.

The experimental part analysed the long-term monitoring data of a two-storey wooden frame and the Filomena Delli Castelli bridge. The wooden frame was placed outside and exposed to variable seasonal environmental conditions. The monitoring period lasted one year, from 10 November 2021 to 2 September 2022, during which no damage was simulated to the wooden frame; thereby, the structure was assumed to remain undamaged. From 2 September to 27 September 2022, damage was gradually induced into a wooden frame by reducing the frame stiffness or mass and increasing the level of damage with each step. Damage was introduced in a non-destructive and reversible manner, with each subsequent damage state including the previous ones to simulate progressive degradation of structural load-bearing capacity. The bridge monitoring period lasted from 30 September 2024 to 6 November 2025. During the monitoring period, the bridge's natural frequency values were obtained under variable external environmental conditions. The experimental data were processed in MATLAB using various statistical and machine learning models. The study analysed regression models using a composite performance metric to assess their applicability for correcting the impact of environmental factors. An important research approach was data segmentation, which divided environmental factors into periods, allowing for a more accurate analysis of the nonlinear

impact and the development of correction functions for ambient temperature, relative humidity, and wind speed separately for each natural frequency. This segmented analysis provided the base for the adaptive selection of regression models.

The validation of the method was performed by comparing structural damage identification before and after applying corrections to the natural frequencies of the wooden frame, using classification accuracy and changes in the number of false positives and false negatives. For the bridge, validation was based on comparing the variance of natural frequency values before and after the method was applied.

The main conclusions of the study were based on the analysis of the data obtained and proposed a structured and implementable approach to reducing the impact of environmental factors for reliable and effective practical implementation of structural health monitoring systems.

Theoretical and methodological basis of the research

The theoretical basis of the Doctoral Thesis is based on several key engineering disciplines, which provide an integrated approach to the assessment of the technical condition of structural elements and the analysis of monitoring data.

The study uses the following engineering disciplines and analytical methods:

- 1) structural mechanics – provides an understanding of structural deformations and load-bearing limit states;
- 2) building structures – analysis of the structural material properties and their behaviour under the impact of environmental factors;
- 3) dynamics – serves as the main theoretical basis for interpreting structural vibrations and changes in natural frequencies under the impact of loads and damage;
- 4) modal analysis – used for quantitative assessment of dynamic properties of structures, including analysis of changes in frequencies, vibration modes, and damping coefficients;
- 5) signal processing – data preprocessing;
- 6) statistical modelling and regression analysis – used to determine the correlation between environmental factors and the dynamic parameters of structures, as well as to assess the efficiency of the methods;
- 7) machine learning methods – used as a basis for modelling the impact of environmental factors, creating adaptive correction functions, and classifying structural damage;
- 8) the structural health monitoring theory – provided the theoretical basis for the development of a monitoring system for damage identification algorithms and their assessment criteria.

The methodological basis of the Doctoral Thesis is based on a data-driven approach, in which data analysis and comparative evaluation of algorithms were used to assess the reliability of the research results. A segmented regression approach, combined with adaptive model selection, was adapted to the range of specific environmental factors. This approach ensures the

determination of a correction function for each natural frequency, thereby deepening the methodological understanding of nonlinear correlation modelling and improving the assessment of the technical condition of vibration-based structures.

Study limitations

The experimental validation of the method developed in the Doctoral Thesis was carried out using a two-storey wooden frame, whose natural frequency values were adjusted to correspond to the frequency values of a five-storey building, as well as using the natural frequency values obtained during long-term monitoring of the Filomena Delli Catelli bridge. The wooden frame model with reduced geometric parameters and homogeneous materials may partially limit the generalizability of the results obtained to multi-storey buildings with complex structural systems and combinations of different materials.

The structural damage simulated in the experiment was introduced gradually and non-destructively, mainly by changing the stiffness and mass of the frame. Although this approach allows for controlled study of the effects of damage, it does not include analysis of material cracking, joint weakening, or other forms of irreversible damage that could occur during actual service.

The developed method is based on the use of unsupervised machine learning algorithms, and its effectiveness depends directly on the quality of the initial training data. The accepted monitoring conditions – data continuity, relatively high measurement frequency, and sensor accuracy – are essential requirements for the effective performance of regression models. In real buildings, irregular data acquisition modes are often observed, and low-quality sensors are used, which in this case can significantly affect the effectiveness of the method.

The study assumed that the dominant environmental factors affecting the dynamic properties of structures are ambient temperature, relative humidity, and wind speed. Other possible factors, such as heavy traffic, pedestrian traffic, or vibrations from nearby sources of excitation, were not considered. Therefore, when applying the method to practical objects, additional corrections and an expanded set of environmental factors may be necessary to ensure a complete interpretation of dynamic parameters in complex service situations.

Results presented for defence

The main results and conclusions obtained in the Doctoral Thesis, which are submitted for defence, are as follows.

- 1. The significant, nonlinear, and seasonally variable impact of environmental factors on the natural frequencies has been demonstrated.***

The Doctoral Thesis demonstrates and quantitatively proves that environmental factors significantly affect the natural frequency values of building structures. The impact of environmental factors on changes in natural frequencies has been determined. The results confirm that environmental factors affecting material mechanical and physical properties must be considered in structural health monitoring.

2. *A segmented regression and nonlinear correction approach for modelling the impact of environmental factors has been developed and validated.*

The selection of the adaptive regression model developed in the Doctoral Thesis is based on a specific segment of environmental factors. Instead of using a single model, multi-level segmentation is applied, selecting the optimal regression model for each segment based on a composite performance metric value. As environmental effects vary seasonally, a segmented approach improves prediction accuracy and effectively separates environmental impact from structural changes.

3. *A new method has been developed to reduce the impact of environmental factors on monitoring data, which improves the accuracy of the damage detection algorithm, ensuring reliable and effective long-term structural health monitoring.*

The Doctoral Thesis develops and experimentally validates a method that reduces the impact of environmental factors, ensuring effective long-term structural health monitoring. The developed method combines data acquisition with machine learning algorithm-based data analysis, enabling automated structural damage identification and improved structural condition assessment. Experimental validation was performed using long-term monitoring data from wooden frame and bridge structures.

4. *Recommendations for the application and implementation of structural condition monitoring in practice under variable environmental conditions have been defined.*

The recommendations and developed method provide a basis for standards and technical specifications for structural health monitoring of different types of structures under varying environmental conditions.

Approbation of the results and publications

The Thesis results have been reported and discussed at three international conferences. The study's main results have been presented in four scientific publications, indexed in the WoS and Scopus databases and in two abstract books of scientific conferences.

Scientific articles in scientific journals indexed in WoS and Scopus

1. Ratnika, L., Gaile, L., Vatin, N. Impact of groundwater level change on natural frequencies of RC buildings. *Buildings*, vol. 11, no. 7, 2021, 265, doi:10.3390/buildings11070265
2. Gaile, L., Pakrastins, L., Ratnika, L. Structural Health Monitoring by merging dynamic response data. *Magazine of Civil Engineering*, vol. 111, no. 3, 2022, doi:10.34910/MCE.111.11
3. Gaile, L., Ratnika, L., Pakrastins, L. RC Medium-Rise Building Damage Sensitivity with SSI Effect. *Materials*, vol. 15, no. 5, Mar. 2022, doi: 10.3390/ma15051653
4. Janeliukstis, R., Ratnika, L., Gaile, L., and Rucevskis, S. Environmental Factors in Structural Health Monitoring – Analysis and Removal of Effects from Resonance Frequencies, *Journal of Sensor and Actuator Networks*, vol. 14, no. 2, Apr. 2025, doi: 10.3390/jsan14020033

Scientific articles in conference proceedings indexed in WoS and Scopus

1. Gaile, L., Sliseris, J., Ratnika, L. Towards SHM of medium-rise buildings in non-seismic areas. International Conference on Structural Health Monitoring of Intelligent Infrastructure: Transferring Research into Practice, SHMII, 2021, June, 1023–1030.
2. Ratnika L., Gaile L., Nicoletti V., Gara F. Multi-dataset OMA and Finite Element Model Updating of Steel Observation Tower, *Journal of Physics: Conference Series*, Institute of Physics, 2024. doi: 10.1088/1742-6596/2647/18/182014

The Thesis results were presented and discussed at the following scientific conferences

1. Ratnika, L., Gaile, L., Nicoletti, V., Gara, F. Multi-dataset OMA and Finite Element Model Updating of Steel Observation Tower. 12th International Conference on Structural Dynamics. Delft, Netherlands, 2–5 July 2023.
2. Ratnika, L. Development of a methodology for instrumented monitoring systems for load-bearing structures in multi-apartment residential and public buildings. RTU 62nd International Scientific Conference, Riga, Latvia, 2021.
3. Gaile, L., Sliseris, J., Ratnika, L. Towards SHM of medium-rise buildings in non-seismic areas. 10th International Conference on Structural Health Monitoring of Intelligent Infrastructure: Transferring Research into Practice, 30 June – 2 July 2021.

Content and scope of the Thesis

The Thesis consists of an annotation, a general description, four main chapters, conclusions and a list of used literature. The volume of the Thesis is 127 pages, including 74 pictures, 8 tables, and 210 literature sources.

The general description section of the Thesis presents the significance of the problem and defines the objective, tasks, and novelty of the Doctoral Thesis. This chapter discusses the importance of structural health monitoring and justifies the importance of implementing methods that reduce the impact of environmental factors on monitoring data. The first chapter provides an analysis of the existing building stock, justifying the importance of long-term structural health monitoring. The second chapter analyses the applicability of machine learning algorithms for structural condition assessment and environmental impact reduction. The third chapter presents the main stages of the developed method for reducing the impact of environmental factors, presenting a segmented environmental impact approach with adaptive regression model selection, which allows to determine the optimal regression model for each segment of environmental factors and each natural frequency, ensuring accurate and automated value correction. The fourth chapter presents the validation of the method for reducing the impact of environmental factors using long-term monitoring data from a wooden frame and bridge. This chapter also analyses the correlations and nonlinear relationships between monitoring data and environmental factors. The results of the validation of the developed method before and after reducing the impact of environmental factors are summarised, and the effectiveness of the environmental impact reduction method is compared. The main conclusions are presented at the final conclusions of the Doctoral Thesis.

CONTENT OF THE DOCTORAL THESIS

1. Assessment of the existing building stock and the necessity of structural health monitoring systems

The new building construction statistics have long served as an important reference point for assessing the development of the construction sector. Changes in these statistics reflect changes in society's needs, as well as changes in demand for different types of buildings and the introduction of modern solutions [3].

The construction of new buildings is closely related to economic development and people's opportunities and preferences to choose to build new buildings rather than renovate existing ones. However, in recent years, there has been a trend towards renovating existing buildings, mainly their load-bearing structures. This is particularly common in the historic centre of Riga and in historic buildings around Latvia. According to data from georiga.lv [4], mainly in the areas surrounding Riga – the Old Town and the city centre – there is a historically and architecturally significant building front, which, in the case of building reconstruction and new building construction, must comply with several requirements for building design in the historical centre of Riga and its protection zone, which define the future development of the area and the protection and development of its cultural and historical heritage. The main task of the Riga historical centre's area planning and preservation and improvement of its architectural structure is to preserve the existing historical buildings, thereby emphasising the necessity of renovating existing buildings rather than constructing new ones.

In the case of reconstruction, the existing structural elements of the building are inspected, and based on the conclusions of this inspection and the decision made by the structural engineer, the load-bearing structures of the building are either preserved or demolished.

In the case of building reconstruction, there is no requirement to monitor the existing structural elements of the building during their service life, but, for example, LBN 217-24 "Geotechnical Design" [5], as well as other standards, state that if the load on existing structural elements is not increased during reconstruction or renovation, the structural analysis scheme is not changed, and no excessive deflections or other signs of structural failure are detected, then calculations of the load-bearing capacity of the structural elements are not required. However, considering possible design and construction mistakes and imperfections, these existing structural elements may be affected by increased loads and possible damage during the building's service life.

According to data available on georiga.lv [6] about buildings and land areas that are causing environmental deterioration, the number of such buildings and land areas is highest in the historical centre of Riga (Fig. 1.1). These buildings are classified according to their impact on human safety. They can be buildings that are completely or partially collapsed and dangerous to human safety, buildings in a potentially dangerous technical condition, buildings in a potentially dangerous technical condition that threatens human safety, as well as environmentally deteriorating buildings.

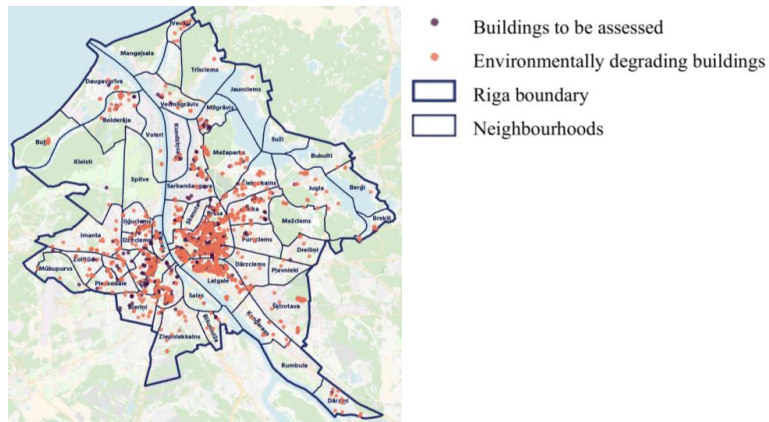


Fig. 1.1. Location of buildings deteriorating the environment in Riga [6].

The large number of buildings classified as environmentally degrading and life-threatening indicates that the technical condition of buildings is deteriorating and, most often for financial reasons, is not being maintained or renovated within a specified period of time, thereby deteriorating the overall technical condition of the building to the stage where it is no longer possible to restore the structural elements.

There are approximately 15 types of standard apartment buildings in the suburbs of Riga and across Latvia [7]. According to Government Regulation No. 907 “Regulations on the Inspection, Technical Maintenance, Periodic Renovation and Minimum Energy Efficiency Requirements for Residential Buildings,” the average service life of these residential buildings is 60 to 70 years [8]. In the European Union, approximately 35 % of buildings exceed a service life of 50 years, which means an increasing demand for their renovation, enhanced monitoring, and reconstruction [9].

LBN 405-21 “Building Technical Inspection Standard” states that technical inspections must be performed periodically, at least once every 10 years, for second and third group public and multi-storey apartment buildings [2]. Consequently, the standard specifies that, for example, buildings inspected in 2019 will have their next technical inspection only after 10 years, and during this period, the building owner is not required to carry out additional monitoring of the building's load-bearing structures.

The deterioration of the technical condition of structural elements depends on various factors: the type of structural material, the type of load to which it is exposed, environmental conditions, and the intended use of the building. However, in practice, structural elements with a service life of 30–40 years are classified as critically deteriorated and require periodic inspection and regular maintenance [10].

Structural health monitoring (SHM) is a method for detecting structural damage that involves observing structures over a period using periodic or continuous measurements. These measurements provide information about the physical or mechanical properties of structures that can be affected by structural damage. The purpose of monitoring the technical condition of structures is to obtain sufficient information about damage to ensure appropriate preventive

measures and renovate structural elements, providing safety for building users. Therefore, damage detection is considered a hierarchical structure, similarly to damage development [11].

For buildings that have reached or are approaching their average service life, it is recommended to monitor the technical condition of structures periodically or over the long term to ensure safe operation and extend their service life. A similar approach is also important in the maintenance of historic buildings, where monitoring would provide an objective assessment of the technical condition of structural elements and enable the planning of maintenance and renovation works [12].

The reliability of structural elements without monitoring systems decreases during their service life, as damage is not detected in time, while maintenance costs increase. In the case of structural elements with monitoring systems, damage is identified at an early stage, maintaining a high level of reliability and stable, lower maintenance costs [10]. In addition, monitoring data allows specifying the impact of loads and the load-bearing capacity of structural elements, reducing uncertainty in safety assessment and ensuring more reasonable decision-making about the technical maintenance of structural elements [13].

Currently, structural health monitoring systems are replaced by visual inspections and various non-destructive testing methods, such as acoustic, ultrasonic, magnetic field, radiography, eddy current, and thermal field methods [10]. These methods ensure high reliability in identifying local damage, but their implementation requires prior knowledge of the location and type of damage [14]. Compared to traditional non-destructive testing and visual inspection methods, structural health monitoring systems provide autonomous data acquisition and analysis, enabling continuous assessment of the technical condition of structural elements in various operating and environmental conditions. However, the implementation of the system is significantly limited by high cost and the requirement to adapt it to each structural element. As a result, structural engineers and building owners often continue to prefer traditional structural monitoring methods in practice [10].

The development of structural health monitoring is closely related to the evolution of digital computing equipment. The recent increase in demand for monitoring the technical condition of structural elements is related to the requirement to ensure human safety, extend the service life of buildings, and optimise structural maintenance costs based on the actual technical condition. Therefore, structural health monitoring is an essential part of sustainable construction and safe infrastructure development [15].

Visual inspection methods for assessing the technical condition of structures are limited in identifying damage to large and complex structures, since they do not provide a quantitative damage assessment and cannot reliably describe the overall technical condition of the structure, especially in cases where the damage is in areas that are difficult to access or invisible. To detect structural damage in such buildings, a vibration-based method was developed, in which structural vibrations are induced by ambient excitations, external excitation sources, or built-in mechanisms [14]. Ambient excitation sources – for example, wind or vibrations induced by heavy traffic – are more cost-effective than forced vibration sources for ensuring continuous, long-term structural health monitoring [16].

The excitation signal of ambient vibration sources varies both in amplitude and frequency spectrum [16]; therefore, operational modal analysis (OMA) is commonly used to determine structural dynamic properties under these conditions, as it enables the identification of the dynamic parameters of a structure in real operating conditions without the use of a controlled excitation source [17]. OMA assumes random, wide-range excitation [18], while experimental modal analysis (EMA) provides high accuracy under controlled conditions.

However, the practical application of EMA for large structures is limited because the use of EMA requires specific equipment, access to structural elements must be ensured, and its implementation involves high costs [19]. Therefore, OMA has become the main method for assessing the dynamic behaviour of large structures [20].

Structural health monitoring based on changes in structural dynamic parameters in buildings and civil engineering structures has been studied since the early 1980s [15]. The main idea of the vibration-based methods is that dynamic parameters, for example, natural frequencies, mode shapes, and damping ratios, depend on the mass and stiffness of the structure, and any damage causes changes in these parameters [14]. Changes in natural frequency are most commonly used to identify structural damage, as they are easier to detect and the measurement error is usually less than 1 % [21], and fewer sensors are required compared to mode shape analysis [14].

Compared to visual inspections and non-destructive testing methods, vibration-based methods provide a global assessment of the structural condition without prior damage location, do not require the placement of sensors near the damage, and allow the use of a limited number of sensors even in large and complex structures [22]. However, practical application of this method is limited by relatively low sensitivity to local damage, measurement uncertainty in the case of higher mode shapes, large amounts of monitoring data, and significant impact of environmental and operational factors on the dynamic parameters of the structure [14].

The data capacity of vibration-based structural health monitoring of load-bearing structures depends on the ability to precisely identify the dominant mode shapes of natural vibration within the measured frequency range. However, in practice, this identification is complicated by the interaction of closely spaced mode shapes and the difficulty of separating individual mode shapes [23], as well as by measurement noise and by measurement data acquisition errors and partial data loss [24]. Consequently, the reliability of vibration-based monitoring results also depends on the ability of the method used to provide stable and consistent structural dynamic parameters, including the dominant natural frequency and mode shapes, in situations with incomplete measurement data and increased structural complexity [25].

In 1993, Rytter first developed a structural damage detection scheme that included damage detection, localisation, severity assessment, and prediction [26]. This scheme is based on a hierarchical approach, where each subsequent level requires information from the previous level, and higher-level analysis usually requires analytical models or structural data examples corresponding to different damage states [15].

The result of structural health monitoring is updated information on a structural element's capacity to continue performing its intended function, considering deterioration and potential damage caused by environmental conditions. The monitoring process includes determining

operational conditions and monitoring objectives, data acquisition and processing, feature selection, and the development of statistical models for damage identification and severity assessment. Statistical models provide answers to key questions regarding the structural health monitoring of buildings. Based on the results of this model development stage, it is possible to identify whether the structural element is damaged, where the damage is located, what type and scale of damage it is, and determine the remaining service life of the structural element, while also assessing possible false damage indications [27].

Structural damage detection is based on comparing the current state with the reference or undamaged state of the structural element to identify statistically significant changes in dynamic parameters [15]. If the reference state is not defined precisely, the results of damage detection may become uncertain, particularly in the case of minor changes in parameters. Therefore, damage identification is formulated as a statistical decision-making problem, where accuracy is closely related to the data quality and the suitability of the assessment methods used [28].

In vibration-based structural health monitoring systems, sensors are used during the data acquisition phase to obtain measurements that describe the dynamic response of the structure. The sensors convert the dynamic response into signals that can be stored and further processed within a data acquisition system (DAS).

Sensor measurements used in structural health monitoring can be divided into kinematic, mechanical, and environmental impact measurements [29].

Sensors are one of the most important components of a monitoring system, as the quality of the data obtained directly affects the accuracy of dynamic parameter determination. Piezoelectric, optical fibre, and microelectromagnetic (MEMS) sensors are used in structural monitoring [14], of which MEMS sensors are the most commonly used devices in structural health monitoring in recent years. MEMS devices can provide stable voltage offsets, amplifying signal charge flows to measurable levels, while maximising the signal-to-noise ratio (SNR), providing the necessary signal processing to filter and extract the required signal, and stabilising sensor operation under different temperature conditions [30].

It is important to consider the specific properties and performance of each sensor manufacturer when selecting the appropriate type of sensor for structural health monitoring. Sensors used for structural health monitoring of buildings and infrastructure must provide high sensitivity and low noise levels [31].

The sensor measurement signal also contains high-frequency and low-frequency components caused by internal sensor noise, electronic components, and environmental disturbances. To reduce noise, filtering is applied during signal processing, improving the signal-to-noise ratio and ensuring more stable identification of natural frequencies in long-term structural health monitoring [32].

High-quality sensors are generally required for vibration measurements. However, over the last few years, high-quality sensors have been used less frequently in favour of a larger number of lower-quality, cheaper sensors that are distributed more widely. For example, it is possible to determine structural vibrations using smartphones with an accelerometer application. Since the sensors built into smartphones are of low quality, noise reduction is achieved by high-

frequency filtering. Filtering improves the efficiency of the system by reducing integrated noise. However, it also creates the risk that important information is removed from the signal [33]. Since 2015, several studies have also used sensors built into smartphones to obtain measurements for monitoring bridge structures [34].

One of the main aspects of structural health monitoring is selecting and extracting the features whose values are affected by damage. Not every feature has significant changes due to structural damage that can be identified even with the most advanced machine learning algorithms [1]. The aim of feature selection is to extract from the data a set of variable features that effectively describe the changes in the dynamic properties of the structure caused by damage, while reducing the impact of noise or insignificant variations, ensuring reliable prediction results [35].

The feature extraction process can be divided into two main groups: data-driven and model-based feature extraction. Additionally, to these two methods, wave propagation-based and mechanical impedance-based methods are also used, which are subsets of data-driven methods. However, these methods are generally not suitable for large civil buildings and infrastructure but are more commonly used in aeronautics and automotive manufacturing as a quality control tool [1].

Model-based methods involve the creation of a finite element model and modal analysis to determine the dynamic parameters. Structural health monitoring in this case is performed by analysing changes in model parameters or prediction errors in model output data, which allows to identify structural damage. This approach is particularly suitable in cases where the amount of monitoring data is limited, but its practical application is significantly affected by the variability of environmental conditions and the requirement to ensure high accuracy of the final element model [1]. Finite element models are used in sensor network design, damage simulation, and for supervised learning of data-driven algorithms [36]. Finite element model accuracy is improved through model updating approaches involving adjustments to the mass and stiffness matrices [37]. Quantitative analysis of dynamic parameter changes due to operational and ambient environmental conditions is essential for both damage assessment and analytical model calibration [38].

Data-driven methods directly use measurement signal analysis and involve feature extraction and decision making about the technical condition of the structure [46]. Feature extraction can be performed in the time, frequency, or time-frequency domain, as well as using machine learning algorithms to process complex signals and identify damage-induced changes in the dynamic parameters of structures.

Considering the advantages and disadvantages of both methods, recent studies increasingly tend to use hybrid methods that combine the advantages of model-based and data-driven methods, improving the accuracy of structural damage identification under varying environmental and operational conditions [40].

The importance of structural health monitoring has been demonstrated and substantiated in several scientific publications; however, its application to existing building structures exposed to environmental conditions remains challenging and requires further research [12] for implementing this method in practice. The main limitations to the practical implementation of

structural health monitoring are economic aspects, the wide diversity of building structural systems, insufficient data on existing buildings, and the impact of environmental and operational conditions on existing structures [41].

Structural damage is considered local, but the localised excitation has only a limited effect on the global dynamic response of the building. For large-scale buildings, ambient excitation is the most effective source of input, providing impulses of sufficient amplitude and a sufficiently broad frequency range to excite mode shapes. However, compared to local impulses, which are stationary, these sources of excitation need to consider the environmental variability [1].

Studies published in 1996 [42] and 1998 [43] present a comprehensive literature review on vibration-based methods for detecting damage in buildings, while also concluding that most of them are based on previously developed analytical models. In addition, the studies were mainly performed in laboratory conditions and did not analyse the dynamic parameters of structures under variable environmental conditions [44].

The impact of environmental factors on the development of structural health monitoring is highlighted as a key research area that affects the reliability and accuracy of current structural health monitoring systems [14].

Environmental conditions include wind, temperature, humidity, and snow. Operational conditions include loading conditions, operating speed, and mass loading. Buildings are simultaneously exposed to various operational and environmental conditions [45]. The impact of environmental factors on the dynamic properties of buildings can be significant and may have a greater effect on dynamic parameters, such as natural frequencies, than structural damage. Therefore, in structural health monitoring, the impact of environmental factors on the structures can be considered as false damage [46].

Most of the research in structural health monitoring focuses on the effects of ambient temperature and wind-induced loads (Fig.1.2). Other impact factors, for example, humidity and changes in boundary conditions, are considered less often [41].

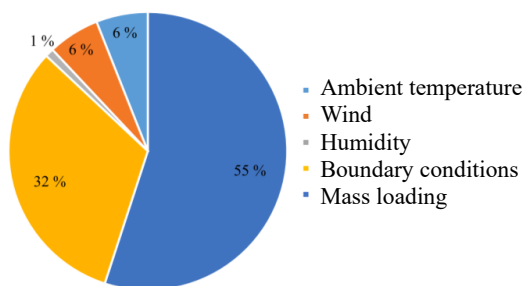


Fig. 1.2. Variation in different environmental factors, whose impact is studied in scientific publications on structural health monitoring [41].

Any changes in environmental factors also affect the material properties of structures. Ambient temperature is one of the main environmental factors affecting the dynamic properties of buildings. The impacts of changes in ambient temperature on materials properties can be classified into three main categories:

- changes in geometric dimensions resulting from thermal expansion and contraction;

- changes in mechanical properties due to variations in the modulus of elasticity;
- changes in boundary conditions and internal forces in statically indeterminate systems.

In structural health monitoring, temperature changes over time must be considered – both daily and seasonal temperature fluctuations.

Wind load is defined by two main components – wind speed and wind direction, which affect the dynamic parameters of a building. During strong wind, the aerodynamic excitation may induce energy input exceeding the building's inherent damping capacity.

Varying relative humidity causes changes in the mass and boundary conditions of the structure, as the material gradually absorbs or loses moisture. These variations result in changes in the mechanical properties of the structure, which are reflected in changes in the natural frequency and other dynamic parameters [47].

Long-term structural health monitoring research indicates that, due to the ambient temperature, relative changes in the natural frequency of structures can exceed 1 %, which can potentially mask changes in dynamic parameters caused by damage [48]. The results of monitoring data from Milan Cathedral and Prague TV Tower confirmed that the ambient temperature is the main environmental factor causing changes in the dynamic properties of structures, while changes in relative humidity and wind have less impact [49]. A similar effect was observed in the structural health monitoring of the Cardarelli Hospital in Campobasso, where changes in natural frequencies were explained by the fact that the two blocks of the building are separated by a joint, and as the ambient temperature rises, the distance between the blocks decreases as a result of thermal expansion, and the connection between the blocks causes a certain increase in rigidity in the longitudinal direction of the building [50].

The groundwater level is also an environmental factor that can impact the dynamic properties of a building [51]. Changes in the groundwater level are caused by precipitation, ambient temperature, the lithological composition of the soil, and the level of drainage [52]. Fluctuations in the groundwater level affect the properties of different soil layers. The depth of the groundwater level from the ground surface affects the bearing capacity and deformation of the soil, as well as the stability and durability of foundations [53].

During the structural health monitoring of buildings and infrastructure, both non-load-bearing structures and soil parameters must be considered when creating the finite element model. By including the impact of the soil in the finite element model, it is possible to observe changes in natural frequency of 21 %, 25 % and 20 % from the reference model, therefore confirming the impact of the soil on the dynamic parameters of the building [54]. Soil type can also be a factor that impacts mode shapes and, in some cases, modifies them, causing vertical vibrations [55]. The influence of soil on dynamic parameters of a building is analysed using elastic foundation analysis. Elastic foundation springs depend on soil type, layer thickness, groundwater level and soil depth [56].

2. Machine learning methods applied to structural health monitoring

Structural health monitoring researchers have increasingly focused on the application of artificial intelligence to enhance the automation of technical condition assessment and maintenance of buildings and civil infrastructure through autonomous, accurate, and robust processing of monitoring data [57].

Feng and Bahng in 1999 [58] were probably the first scientists to apply a back-propagation neural network to determine the reduction in stiffness caused by damage, based on the dynamic properties obtained from the vibrations of cyclically loaded reinforced concrete columns.

The application of machine learning methods in various research fields is still being studied to improve the learning process, with a focus on data dimensionality reduction [59]. Various structural health monitoring systems are capable of fast acquisition, transfer, and storage of large amounts of data. However, the amount of data in these networks is so large that ensuring the data quality, consistency, and reusability, as well as reliable decision-making based on the data obtained, is one of the most pressing issues.

There is an increasing necessity to use new technologies to automate data analysis processes and improve the accuracy of these processes [60]. An automated and intelligent system operating in a variable environment must be capable of learning. Therefore, if the system can learn and adapt to changes, the system developer does not need to predict and provide all possible solutions to situations [61].

Machine learning algorithms are necessary not only to process large amounts of data but also to identify various outliers and errors in measurements. In some cases, certain structural dynamic parameters may not correspond to general data models and may be considered as anomalies. These anomalies can be caused by a variety of reasons and may include measurement error, for example, signal drift, decreased accuracy, or full data acquisition disruption. Therefore, an automated method is necessary to accurately classify these anomalies and evaluate the technical condition of structural elements [62].

The main assumption of automated methods is that damage – cracks, progressive deterioration of the structure – is characterised by data anomalies or deviations from the normal state that can be recognised. If the data analysis identifies possible deviations, specially developed algorithms can be used to localise structural damage and determine the type and level of damage [63].

The aim of **machine learning algorithms** is to identify statistical patterns in data [64] and provide the ability to automatically learn and improve based on the information obtained, without being directly programmed. Through the learning and improvement process, the system automatically learns the relationships between feature patterns and results.

The tasks performed by the machine learning algorithms can be summarised as follows:

- 1) classification – the aim is to determine which category the output data belong to;
- 2) regression – the aim is to establish a relationship between numerical outputs and multiple input variables;
- 3) prediction – the aim is to predict future values within a specified period of time;
- 4) clustering – the aim is to divide the output dataset into clusters with similar patterns [65].

Based on literature published over approximately two decades up to 2007, seven axioms were formulated in a study [66] that define the basic principles of damage detection. Axioms state that structural elements always have material imperfections or defects, but damage assessment is only possible when comparing two states of the system. Sensors do not directly measure damage, so damage identification requires the extraction of features from measurement data using signal processing and statistical methods. The location of damage can be determined using unsupervised learning, but supervised learning is required to determine the type and severity of the damage. At the same time, the accuracy of damage detection is affected by noise, environmental and operational conditions, the time and spatial scale of the sensor system, and the frequency range of the excitation, which determines the extent of the damage that can be identified. These axioms became a significant foundation for further research on the integration of structural health monitoring and machine learning methods [66].

Most of the research in the field of machine learning focuses on the development, characterisation, and analysis of general learning methods, emphasising the generality of the methods and the analysis of their effectiveness [67].

Machine learning algorithms can be divided into four groups: supervised, unsupervised, semi-supervised, and deep learning algorithms.

The most used methods are supervised, unsupervised, and semi-supervised machine learning. Unsupervised machine learning algorithms are used for large and complex buildings and civil infrastructure when there is insufficient data available on damaged structures. In cases where data are available for both damaged and undamaged states of buildings and civil infrastructure, supervised machine learning methods are most commonly used [1].

The selection of a machine learning algorithm for a given structural health monitoring task depends on whether the problem requires supervised or unsupervised learning [68].

Supervised learning is based on a labelled training dataset and uses classification methods to establish a relationship between observations and their corresponding output data labels, enabling the classification of new, previously unseen data.

Semi-supervised machine learning algorithms are used in cases where a limited amount of labelled data is available. These algorithms use the information from the labelled data, while the unlabelled data is used to further constrain the classification model [69].

Unsupervised learning is used in cases where no labels are available for the input data. The method attempts to classify the input data based on their similarity, grouping similar observations into clusters or identifying anomalies to determine data points that differ significantly and may indicate structural damage, noise, or environmental impact [70]. In most cases, anomaly detection methods assume that the normal state forms a single class or cluster, and points outside the cluster boundaries are labelled as new or anomalies (Fig. 2.1). If the data form several groups due to different undamaged or damaged states, cluster analysis is considered the most appropriate method.

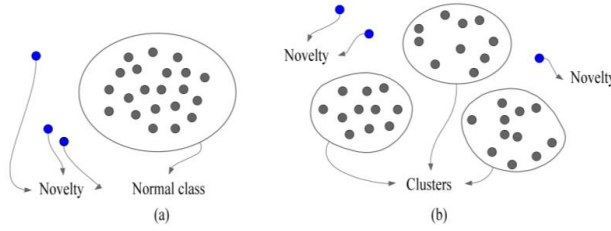


Fig. 2.1. Novelty detection methods: a) one-class classification; b) multi-class clustering analysis [71].

Deep learning machine algorithms are capable of automatically performing feature extraction and learning hierarchical, high-level feature representations, which allows them to effectively solve complex tasks by dividing them into a large number of simple problems [96].

Machine learning algorithms are selected for a given problem situation based on several criteria. Some of the factors that affect the choice of algorithm include, for example, the amount of training data, the expected training time, and the level of accuracy [1].

The main factor in choosing a machine learning method algorithm is also the expected result – the level of damage identification in structural health monitoring. The limitations of each method and the requirements for structural health monitoring in terms of damage detection levels and operating conditions must be considered when selecting a machine learning method [40].

Artificial neural networks (ANN) are used in structural health monitoring to learn data representations and reduce data dimensions, often based on supervised learning with data from an undamaged state to identify deviations and possible damage. Classic ANNs are characterised by a simple structure with a small number of hidden layers. These networks are commonly used to reduce data dimensions.

A convolutional neural network (CNN) is a deep learning approach that automatically identifies the most significant features in data using convolution filters. CNNs are most commonly used for data analysis with a network structure and local spatial correlation.

The support vector machine (SVM) method is widely used in classification and regression tasks, determining the optimal boundary between data classes and identifying both linear and nonlinear relationships between data using various kernel functions [40].

Principal component analysis (PCA) is used to reduce the dimensions of data, preserving only the most important information from the original data and improving learning efficiency by reducing data acquisition time [40], [72]. Kernel principal component analysis (KPCA) is used for the analysis of nonlinear relationships, enabling the effective analysis of complex data structures [73].

Environmental factors can impact the dynamic properties of structures in different ways, for example by increasing or decreasing natural frequencies. To improve the accuracy and reliability of structural health monitoring, various machine learning algorithms are used to reduce the impact of environmental factors [41]. Table 2.1 summarises several machine learning algorithms, their applications, and specific environmental factors whose impact has been analysed in this study.

Table 2.1

Machine learning algorithms used in publications to reduce the impact of environmental factors

Machine learning algorithm	Application	Analysed and corrected environmental factor
Principal component analysis (PCA)	Using PCA-transformed environmental factors, the composite ensemble learning model more accurately predicted the correlation between dynamic parameters and environmental factors, enabling indirect removal of the environmental impact by analysing prediction residuals [74].	Ambient temperature, relative humidity, wind speed, wind direction, surface temperature
Autoregressive models with exogenous inputs (ARX)	Autoregressive models (ARX) were used to predict natural frequency variations of the Z24 bridge while considering changes in ambient temperature [75].	Ambient temperature
Gaussian process regression (GPR)	GPR algorithm was used to predict the natural frequencies of wind turbine blades, considering the influence of environmental factors [76].	Ambient temperature
Principal component analysis (PCA) and model-agnostic meta-learning (MAML)	PCA was used to remove some less significant variations from the frequency data. MAML was used to adapt models to different environmental conditions and structures, improving the system's ability to adapt to variations in the environmental conditions [77].	Ambient temperature
Convolutional neural networks (CNN) and Gaussian mixture models (GMM)	Instead of directly separating individual environmental factors, GMM learned the statistical distributions of features extracted by CNN, allowing the model to filter out environmental impacts and focus on detecting structural damage [78].	Ambient temperature
Bayesian model updating	The method was used to adapt the temperature correction function semi-automatically to reduce temperature-induced errors [79].	Ambient temperature
A model-based approach	Temperature modelling was integrated into the finite element model to separate structural damage from changes caused by the environmental conditions [80].	Ambient temperature

A method in which **principal component analysis (PCA)** is used to reduce the dimensions of environmental factors and a composite ensemble learning approach is used to predict dynamic parameters [74], is based on data-driven indirect reduction of environmental impacts by analysing prediction errors between measured and predicted natural frequencies.

The method allows several environmental factors to be considered simultaneously and describes nonlinear relationships, but its effectiveness depends on the quality of the training

data and the assumption that the relationships remain unchanged over time. The reliability of the method is limited, and its validation was based on short-term monitoring data from a full-scale grid structure, in which no abrupt changes in environmental factors were observed [74].

A method based on reducing the impact of environmental factors using data-driven **autoregressive models (ARX)** [75] describes changes in the natural frequencies as a function of ambient temperature, using long-term monitoring data obtained by automated modal analysis (AMA). The impact of the environmental factors is indirectly compensated by analysing the prediction residuals between the measured and ARX model-predicted natural frequencies.

The method was validated using long-term monitoring data from a full-scale bridge structure, confirming its applicability to other engineering structures under variable ambient temperature. However, only positive temperature values were used in the analysis to reduce the impact, without considering changes in the dynamic parameters of the structure at negative ambient temperature values, and the method is based on empirical models with limited interpretation.

The method using **Gaussian process regression (GPR)** [76] is based on the indirect removal of environmental factors by modelling the relative correlations between the dynamic parameters of nominally identical structural elements. Assuming that the impact of the environmental factors on these elements is similar, GPR is used to model the functional correlation between the dynamic parameters of the two elements, and the impact of the environmental factors is compensated for by analysing the prediction residuals.

The advantage of this method is the modelling of nonlinear correlations with uncertainty assessment, while its limitations are related to its applicability only to nominally identical elements, the assumption of similar impact of the environmental factors, and high dependence on the quality of the undamaged state training data.

The method using **meta-learning (MAML)** and **principal component analysis (PCA)** [77] is based on indirectly reducing the impact of ambient temperature by modelling the dynamic response of the structure as a function of temperature.

High-dimensional feature data is reduced using principal component analysis (PCA), while the meta-learning algorithm (MAML) is trained using numerically simulated finite element models with different temperature-stiffness scenarios. The method allows for an indirect reduction of the impact of ambient temperature even in situations where data is limited, but it only analyses the temperature impact factor and has been validated on numerically simulated finite element models, which limits its direct application to buildings and civil infrastructures in variable environmental conditions.

The method using **convolutional neural networks (CNN)** and **Gaussian mixture models** [78] is based on automatic feature extraction from measurement signals and indirect reduction of the influence of ambient temperature by describing the distribution of features with a Gaussian mixture model (GMM). The impact of the ambient temperature is modelled statistically by comparing the distributions of the reference and monitoring conditions using Kullback-Leibler (KL) divergence.

The advantage of this method is that it reduces the impact of ambient temperature without directly measuring the environmental factor during monitoring. However, the limitations of the

method are related to the large amount of training data required, limited interpretation and validation in laboratory conditions on reduced-scale structures.

The method based on the **Bayesian model update** [79] simulates the impact of ambient temperature as a temperature-dependent transfer function of the measurement system, which is used for direct correction of the measured data. The impact of ambient temperature is described by an empirical second-order polynomial, whose coefficients are adaptively updated using Bayesian model updating.

The method provides direct and interpretable correction for the impact of ambient temperature, with the ability to adapt to temperature variations during the monitoring period. The limitations of the method are related to the fact that only the impact of ambient temperature is analysed, its practical implementation requires controlled temperature calibration, and the method has been validated under laboratory conditions on a reduced-scale experimental system.

The method using a **model-based approach** to reduce the impact of environmental factors [80] directly integrates the impact of ambient temperature into the finite element model, while modelling both temperature and damage-induced changes in the dynamic parameters of the structure. The impact of temperature is assessed by modelling the dependence of the material's modulus of elasticity and thermal expansion on temperature, ensuring a physically justified separation of environmental impacts without direct measurement signal correction.

The main advantage of this method is the high interpretability of results and the physically justified reduced impact of ambient temperature. The limitations of the method are related to the fact that only the impact of ambient temperature is analysed, high dependence on the availability of an accurate finite element model, and validation performed using numerical simulation data.

The analysed methods for reducing the impact of environmental factors allow for a significant decrease in changes in dynamic parameters caused by the environmental conditions, while ensuring sensitivity to structural damage. However, their practical application is often limited by assumptions about the stability of the environmental conditions, the quality and quantity of training data, limited interpretability, and the fact that most studies only analyse the impact of ambient temperature and validation is based on short-term or finite element model-simulated monitoring data.

Considering the limitations mentioned above, existing methods for reducing the impact of environmental factors are not completely suitable for long-term structural health monitoring of buildings and civil infrastructures. During the service life of buildings and civil infrastructures, their structures are simultaneously affected by several environmental factors, for example, relative humidity, wind speed, precipitation, and snow, the impact of which varies significantly over time in both character and intensity [81]. Therefore, it is necessary to develop an adaptive, easily interpretable method that allows to reduce not only the impact of ambient temperature but also other environmental factors on the dynamic properties of structures, while maintaining high sensitivity to structural damage and ensuring practical applicability in long-term structural health monitoring conditions.

3. Method to reduce the impact of environmental factors on natural frequency monitoring data

To ensure the efficiency and reliability of the structural health monitoring system, a method for reducing the impact of environmental factors was developed, which consists of eight subsequent steps (Fig. 3.1), allows stable and comparable natural frequency values to be obtained and improves damage identification. The method ensures the quantification and correction calculation of environmental factors, is practical, can be integrated into monitoring system algorithms, and provide the ability to adapt to seasonal climate changes.

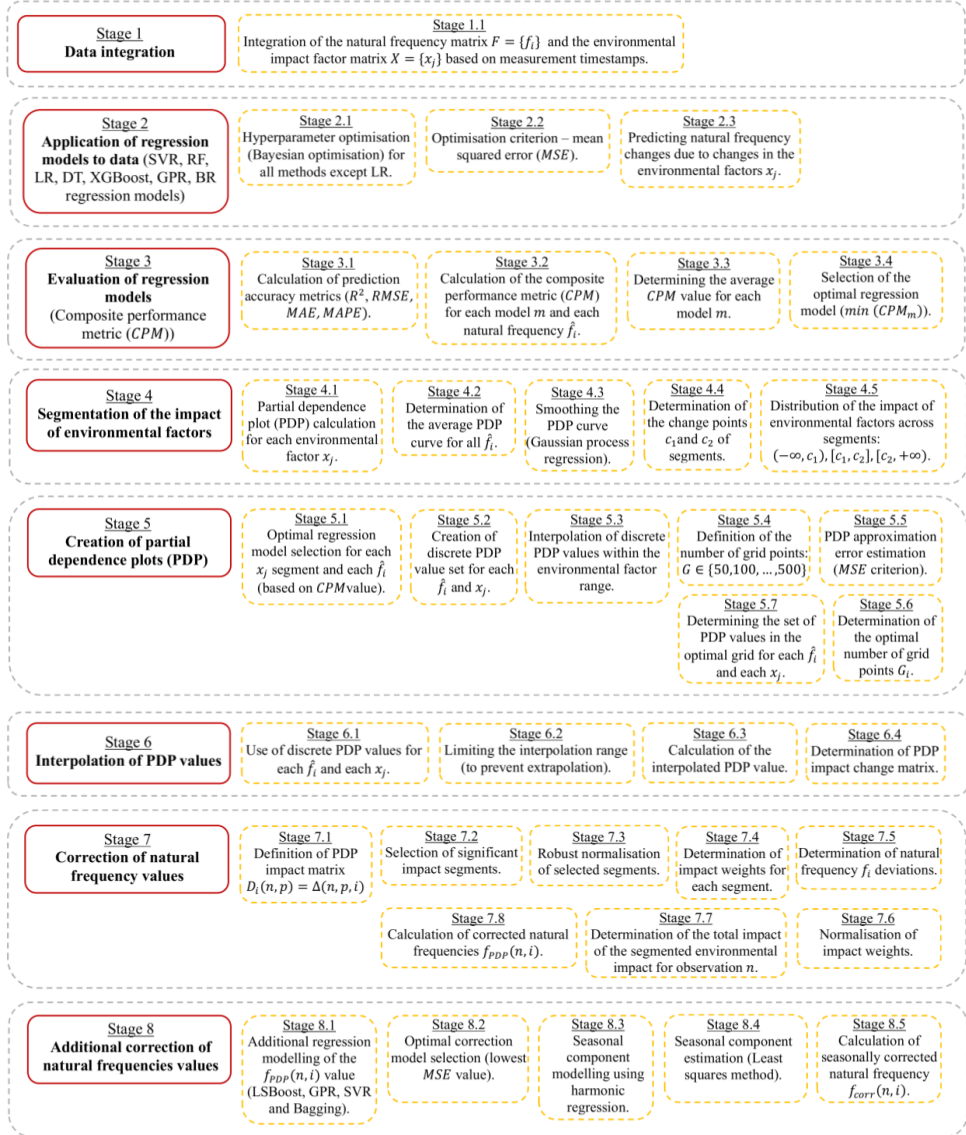


Fig. 3.1. Method for reducing the impact of the environmental factors, Stages 1–8.

In **Stage 1** of the method for reducing the impact of environmental factors, the natural frequency measurement data and environmental factor data are combined into a single dataset. The data is combined according to the measurement time stamps, ensuring that each natural frequency measurement is assigned the values of environmental factors measured at the same time. The result is a combined data matrix, where each row characterises the dynamic response of the structure under specific environmental conditions. This step provides the basis for further analysis and the development of correction models.

In **Stage 2**, seven different regression models are used to reduce the impact of environmental factors, to model the dependence of each natural frequency on environmental factors: support vector regression (SVR) with a Gaussian kernel function, random forest regression (RF), linear regression (LR), decision tree regression (DT), gradient boosting regression (XGBoost), Gaussian process regression (GPR) with a Matern 3/2 kernel function, and Bayesian regression (BR) with a Matern 5/2 kernel function. The use of different models provides an opportunity to compare the quality of predictions and identify which is the most appropriate method for a specific dataset [82].

Support vector regression (SVR) is an adaptation of the support vector machine (SVM) algorithm for regression tasks, which allows modelling nonlinear relationships using Gaussian or radial basis function (RBF) kernel functions [83] and allows supervised outliers within a specified tolerance interval [84].

Random forest regression (RF) is an ensemble learning method that combines multiple decision trees trained on randomly selected data samples and variable subsets, providing stable predictions and reducing the risk of overfitting [85].

Linear regression (LR) assumes a linear relationship between natural frequencies and environmental factors, minimising the mean squared error. The method is suitable for cases with approximately linear relationships [86].

Decision tree regression (DT) divides the data domain into regions with similar predictions, minimising the error in each domain. However, the accuracy of the method may decrease in the case of complex nonlinear relationships [87].

Gradient boosting regression (XGBoost) is an ensemble learning method that sequentially improves decision trees, limiting model complexity and reducing the risk of overfitting through regularisation [88].

Gaussian process regression (GPR) is a nonparametric method that models nonlinear relationships using a Gaussian process model with a specific covariance structure and allows quantitative assessment of prediction uncertainty [89].

Bayesian regression (BR) in this case is based on GPR with automatic relevance determination (ARD) Matern 5/2 kernel function, which assigns a separate length scale parameter to each input parameter and provides accurate predictions with a quantitative assessment of uncertainty [90].

To ensure optimal model fitting, Bayesian optimisation is used to automatically search for the best model hyperparameters, improving the agreement between the predicted natural frequency and the observed data, considering environmental factors. During the optimisation process, a probabilistic surrogate model of the objective function is created using Gaussian

process regression (GPR), which allows both the mean value and variance of the prediction to be estimated [90].

Bayesian optimisation is applied to each regression method by performing 30 hyperparameter tests to find the optimal hyperparameters (SVR – regularization parameter and kernel function parameter; RF – number of decision trees, maximum number of splits, minimum leaf size, and minimum number of samples per node before splitting; XGBoost – learning rate, number of gradient boosting trees, maximum number of splits, minimum leaf size; GPR – kernel function type, length scale, and signal variance; BR – ARD length value; DT – maximum number of splits and minimum leaf size).

The optimisation problem is formulated as the selection of a hyperparameter vector that minimises the mean squared error (MSE). The next combination of hyperparameters is selected using the expected improvement plus (EI+) acquisition function, considering both the possible reduction in prediction error and the related uncertainty [91].

Methods for reducing the impact of environmental factors in **Stage 3** involve assessment of the accuracy of each model to analyse the model's ability to adapt to data and provide accurate predictions. Four main metrics are used: coefficient of determination (R^2), root mean squared error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE).

The R^2 value describes the proportion of the variance of the dependent variable explained by the model ($R^2 = 1$ – perfect fit, $R^2 = 0$ – the model does not outperform the average prediction, $R^2 < 0$ – worse than the average prediction). RMSE and MAE describe the average prediction error, while MAPE expresses the error as a percentage, and lower RMSE, MAE and MAPE values indicate higher model accuracy [87].

Composite performance metric (CPM) is calculated for each model, combining R^2 , RMSE, MAE and MAPE values to provide a single metric that can be used to compare the overall accuracy of different regression models. CPM is calculated using the following formula:

$$CPM = M_{norm}(RMSE) + M_{norm}(MAE) + M_{norm}(MAPE) - M_{norm}(R^2), \quad (3.1)$$

where $M_{norm}(M_m)$ means that the corresponding indicator is normalised according to the formula

$$M_{norm}(M_m) = \frac{M_m - \mu_M}{\sigma_M + \varepsilon}, \quad (3.2)$$

where M_m is the *RMSE*, *MAE*, *MAPE* or R^2 value of a particular model metric; μ_M is the average value of the corresponding indicator, calculated across all models at the analysed frequency; σ_M is the standard deviation of the corresponding indicator; and ε is a very small constant added to avoid division by zero and improve numerical stability [92].

A lower CPM value indicates better model performance. The model with the lowest average CPM value is selected to identify the environmental factor segments.

The impact of environmental factors on natural frequencies may vary across different ranges. To adjust the frequency values more accurately, the segmentation principle is used in **Stage 4** of the method for reducing the impact of environmental factors, where the monitoring data is divided into several segments according to the nature and dynamics of changes in environmental factors.

The monitoring data for ambient temperature, relative humidity, and wind components are divided into three segments corresponding to low, medium, and high levels of the corresponding environmental factor. This approach provides the opportunity to analyse possible nonlinear relationships across different ranges of environmental factors. Each segment contains enough data for stable regression model training, thus avoiding the risk of over-dividing and overfitting the models [93].

The correction of natural frequencies is applied to each segment separately, with segment boundaries determined automatically using the partial dependence plots (PDP) curves of the selected regression model. PDP describes the predicted frequency changes depending on only one selected environmental factor, while keeping the remaining factors at their observed values across the entire dataset. The partial dependence function is calculated as the average value of model predictions for all observations, replacing the value of the factor being analysed with a specific grid point, while keeping the values of the other environmental factors as they are measured:

$$f_{PDP(x_j)} = \frac{1}{N} \sum_{n=1}^N f(x_j, X_{-j}^n), \quad (3.3)$$

where x_j is the value of the analysed environmental factor, X_{-j}^n represents the actual measured values of remaining environmental factors for the n -th data observation, and N is the number of monitoring observations [94].

Based on the assessment of the regression models performed in Stage 3, the model with the lowest CPM value is selected. Using this model, the average PDP values for all natural frequencies are determined, and the average PDP function is obtained from them. The obtained average function is further smoothed using Gaussian process regression to obtain a smooth and stable description of the relationship. Smoothing is essential because it ensures that segment boundaries are determined from the relationship between the common environmental influence factor and the natural frequency, rather than from local deviations [90].

To determine the segment change points, the MATLAB command *findchangepts* is used, which finds the values of the environmental factors c_1 and c_2 at which the linear trend of the PDP curve changes and the function is optimally separated into three linear segments. Segment change points are selected by minimising the total sum of squared residuals. Once the change points are identified, the range of environmental factor values is divided into three intervals:

$$(-\infty, c_1), [c_1, c_2], [c_2, +\infty). \quad (3.4)$$

In **Stage 5**, regression models are assessed for each environmental factor x_j separately in each segment to identify the regression model that provides the most accurate predictions in the specific range of environmental factors. To evaluate the accuracy of the regression models, the monitoring data is divided into segments using the change points c_1 and c_2 determined in Stage 5. All seven regression models are evaluated in each segment by calculating R^2 , $RMSE$, MAE , $MAPE$ and composite performance metric (CPM). The model with the lowest CPM value is selected as the best in each segment and is used to create a partial dependence plot (PDP) for each natural frequency f_i and each environmental factor x_j . The partial dependence plot (PDP) of reduced values is created in a discrete grid, where the corresponding predicted natural

frequency value is calculated for each point of the environmental factor, with the other factors fixed at their average values.

The optimal number of grid points G_i for each natural frequency is determined using an iterative grid search process with a convergence criterion. The quality of the discrete values is evaluated by calculating the mean square error MSE. After each grid calculation, the values of the discrete partial dependence plot (PDP) are interpolated into the actual values of the environmental factors, and the mean square error between the actual and predicted natural frequency is calculated. If the change in the mean square error (MSE) between two consecutive grids is less than the tolerance ε , the optimal number of grid points is determined. The optimisation process uses a minimum number of grid points $G_{min} = 50$, a maximum number $G_{max} = 500$, and a grid increase step $\Delta G = 50$. Optimally selected discretisation ensures that the interpolated PDP curve accurately reflects the impact of environmental factors and is used for further correction of natural frequencies.

In **Stage 6**, segmented discrete partial dependence (PDP) values are used for each natural frequency f_i and each environmental factor x_j , which are interpolated at the actual environmental factor value in the relevant segment. To avoid extrapolation, the environmental factor value is limited by the minimum or maximum limit value of the segment grid [95].

The interpolated partial dependence plot (PDP) value is then calculated at the relevant environmental factor value. Piecewise cubic Hermite interpolation (PCHIP) is used for interpolation, which forms a smooth, continuous interpolation curve, preserving the smooth nature of the original data and not introducing artificial local oscillations between grid points [96].

As a result of the calculations, an impact change matrix is obtained:

$$\Delta(n, s, j, i) = \hat{f}_{i,j,s}^{PDP}(n) - \hat{f}_{i,j,s}^{PDP}(\bar{x}_{j,s}), \quad (3.5)$$

where $\hat{f}_{i,j,s}^{PDP}(n)$ is the interpolated partial dependence plot (PDP) value at the actual $x_j(n)$; $\bar{x}_{j,s}$ is the mean value of the segment grid; $\hat{f}_{i,j,s}^{PDP}(\bar{x}_{j,s})$ is the value of the segment mean value level [88]. The quantity $\Delta(n, s, j, i)$ represents the change in the i -th natural frequency or deviation from the segment mean value level caused by the deviation of the environmental factor x_j in a particular observation [97].

In **Stage 7** of the method for reducing the impact of environmental factors, a non-negative impact vector w_i is determined for each natural frequency. First, a partial dependence plot (PDP) impact matrix is defined, which summarises the relative impact of each environmental factor and segment at a unified optimisation level [98]. Only those segments in which a non-zero impact occurs frequently enough are selected from the impact matrix D_i using the minimum coverage criterion ($p = 0.05$). To ensure comparability between segments with different scales, the robust normalisation of the selected segments is performed using the interquartile range (IQR) [99].

The impact weights are determined by solving a regularised non-negative least squares optimisation problem, where the deviation of each natural frequency from its mean value is described as a linear combination of segmented environmental impact components, while Tikhonov regularisation reduces the risk of overfitting. After optimisation, the weights are

“returned” to their original scale (by removing the interquartile range (IQR) normalisation) and placed in the full weight vector w_i . To ensure interpretability, the weights are normalised.

The total impact of the segmented environmental factors in each observation is determined by calculating the sum of all segmented environmental impact component values for the relevant natural frequency, each multiplied by the calculated impact weight.

The corrected natural frequency value after Stage 7 is calculated using the formula

$$f_{PDP}(n, i) = f(n, i) - \hat{e}_i^{PDP}(n) = f(n, i) - \sum_p w_i(p) \times D_i(n, p). \quad (3.6)$$

This step removes the impact of the segmented partial dependence plot (PDP), while the weight vector w_i allows for a quantitative interpretation of which segments and which environmental factors dominate the impact of changes in natural frequencies [75].

In **Stage 8** of the method for reducing the impact of environmental factors, additional regression models (LSBoost, GPR, SVR, and Bagging (Bootstrap Aggregating)) are trained on the corrected values $f_{PDP}(n, i)$ to assess the remaining nonlinear or complex environmental impacts.

LSBoost and Bagging describe local nonlinear relationships and increase the stability of predictions [88]. GPR provides residual impact modelling using a probability distribution [90]. SVR, however, is appropriate in cases where residual impacts are weak but remain systematic in character [84]. Consequently, the use of these methods after the initial correction allows for an additional reduction in the impact of environmental factors and operating conditions, while reducing the risk of overfitting [45].

The time-block cross-validation MSE is calculated for each method, and the model with the lowest MSE value is selected. The predicted residual impact of the environmental factors is calculated from the segmented PDP corrected frequency values to obtain an intermediate corrected natural frequency value with reduced segmented and nonlinear impacts, while keeping the seasonal (long-term periodic) impact.

In the next step, seasonality is removed using harmonic regression. The seasonal component is estimated using the least squares method, and the seasonally corrected natural frequency is calculated using the formula

$$f_{corr}(n, i) = f_2(n, i) - SK(n, i) + \overline{SK(i)}, \quad (3.7)$$

where $f_2(n, i)$ is the corrected natural frequency in a specific observation series after correction for the impact of environmental factors; $SK(n, i)$ is the value of the seasonal component for the n -th observation and the i -th natural frequency; $\overline{SK(i)}$ is the average value of the seasonal component, which ensures that the average level of the corrected natural frequency is maintained [100].

The frequency values obtained after removing seasonal impacts no longer contain repeated annual seasonal fluctuations, which improves the sensitivity of structural damage detection. If seasonal impacts are not removed, periodic changes dominate the remaining data, reducing the monitoring system's ability to identify damage [101].

4. Validation of the method for reducing the impact of environmental factors

Long-term monitoring data from two different structures – a two-storey wooden frame and the Filomena Delli Castelli bridge – were used to validate the method for reducing the impact of environmental factors. This study used monitoring data from the Filomena Delli Castelli Bridge obtained in a similar study [102], as the structures of this bridge have been continuously monitored for dynamic data since the study was conducted. In turn, the monitoring data for the wooden frame structure, which was previously analysed in the study [103] in terms of the impact of environmental conditions, is repeatedly analysed in this study using the developed method for reducing the impact of environmental factors.

Experimental monitoring data, using a prefabricated two-storey wooden frame, were obtained between 10 November 2021 and 27 October 2022. The geometry of the two-storey wooden frame was chosen to approximate the real conditions of the objects of study and the dynamic parameters characteristic of medium-height buildings. The dimensions of the two-storey wooden frame in the plan are 705×584 mm, and the total height of the frame is 1.2 m (Fig. 4.1(a)). The main elements of the wooden frame were 15×15 mm wooden slats as the frame's load-bearing columns and a 4 mm-thick wood fibre board as the frame's ceiling slab.

Various levels of damage were induced in the two-storey wooden frame, causing changes in stability and/or mass (Fig. 4.1(b)). In this study, the term “damage” refers to a change in boundary conditions that affects the stiffness of the joints and the dynamic parameters of the structure, not just degradation. The data on damaged structures were obtained between 2 September 2022 and 27 October 2022.

During the experiment, the wooden frame was placed 4.5 km from the Baltic Sea and 10 m from the driveway, providing variable environmental conditions and the impact of nearby traffic. In winter, the wooden frame was covered with a temporary roof to prevent snow load. During the experiment, the wooden frame was protected from direct wind exposure, so wind is not included in the analysis of environmental factors in this case.

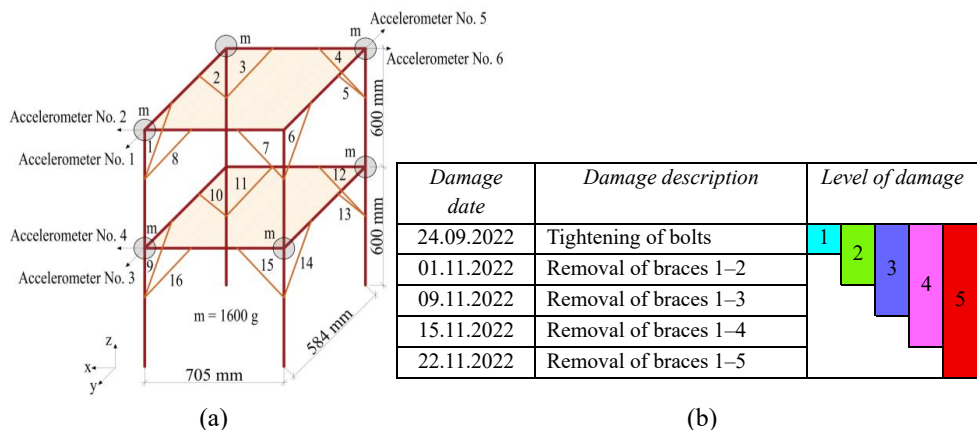


Fig. 4.1. Experimental wooden frame: (a) – model scheme; (b) – description and level of damage to the model.

The measurements were obtained using six Dytran IEPE piezoelectric acceleration sensors (DY 3191A1, 10 V/g, operating range from -51°C to 121°C), connected to a DT9857E data acquisition system (output range $\pm 10\text{ V}$) with 15 m long polyurethane and 2-pin(F) signal cables. The sensors were placed at three connection corners in two horizontal directions – x and y directions. Each sensor weighs approximately 800 g. To ensure the stability of the wooden frame, an additional mass of 1.6 kg was mounted at the corners of the frame. During the experiment, continuous data measurements were taken at a sampling frequency of $f_s = 400\text{ Hz}$.

Weather data during the experiment were obtained from the nearest weather station, including ambient temperature, relative humidity, and precipitation. The ambient temperature during the observation period ranged from approximately -15°C in the winter months to $+30^{\circ}\text{C}$ in the summer months. Relative humidity ranged from 30 % to 100 %, with most observations in the range above 60 % and higher values in the winter months. Precipitation was minimal during the winter period, while in summer it reached its maximum, especially in July, with precipitation amounts ranging from 20 mm to 25 mm per hour.

The acceleration data obtained in the experiment were divided into 30-minute time series. These time series were then separated, filtered into frequency bands, and the raw data were used in the Eigenvalue realisation algorithm (ERA) to determine the frequencies of the first six mode shapes of the wooden frame: transverse f_1 , longitudinal f_2 , and torsional f_3 corresponding to the first bending-torsional mode shape, as well as transverse f_4 , longitudinal f_5 , and torsional f_6 corresponding to the second bending-torsional mode shape.

The first three natural frequencies show significant fluctuations during the winter months, followed by a steady decrease until spring, and a relatively stable period until the first damage. After structural damage, all three first natural frequency values become unstable, with the most significant changes observed after structural damage No. 5. The second three natural frequencies also show periods of fluctuation during the winter months, and until the beginning of damage No. 1, the frequency value zone can be considered stable with less pronounced fluctuations. The highest frequencies after structural damage are characterised by larger amplitudes and more significant decreases in values. However, the f_4 frequency shows smaller fluctuations and a gradual decrease.

To assess whether the natural frequency data follow a normal distribution, the empirical distribution for each frequency was analysed and compared with the theoretical probability density function of the normal distribution, calculated using the mean and standard deviation of the relevant frequency. The results indicate that the distributions of all six natural frequency values differ significantly from the normal distribution. In most cases, the data distributions are asymmetrical and have higher density areas, indicating unequal distribution areas.

To validate the method of reducing the impact of environmental factors using long-term monitoring data of civil infrastructure, the dynamic parameters of the Filomena Delli Castelli bridge structure obtained experimentally were used. The bridge is in Italy; it crosses the Saline River and connects the cities of Montesilvano and Citta Sant'Angelo. The monitoring data were obtained during the period from 30 September 2024 to 6 November 2025.

The Filomena Delli Castelli Bridge is a steel-concrete composite multi-span cable-stayed bridge with a total length of 188.6 m and a width from 19.2 m to 22.8 m (Fig. 4.2). The bridge's

load-bearing structures are 1.2 m high double-T beams connected by double-T crossbeams with a variable height ranging from 0.8 m to 1.2 m. The bridge deck consists of a 25 cm thick reinforced concrete slab. The bridge pylon structures consist of four inclined steel tubes with a diameter of 1.9 m, the lower part of which is filled with concrete at a height of 16 m. Each pylon foundation is supported by 35 m-long drilled piles with a diameter of 1.2 m. The abutment foundations consist of 16 drilled piles with a diameter of 1.2 m, arranged in three transverse rows. The piles support a rectangular foundation slab 1.4 m thick with dimensions of 10.3×16.3 m [104].

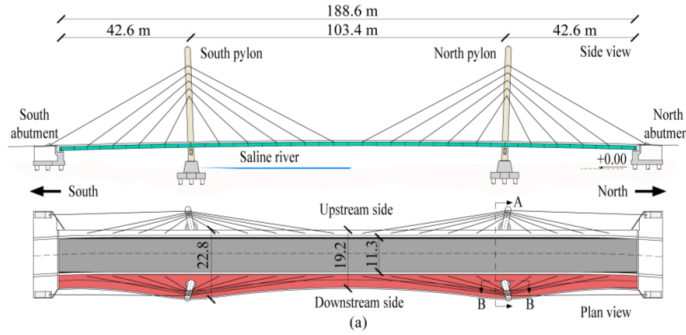


Fig. 4.2. Structural scheme and main dimensions of the Filomena Delli Castelli Bridge: (a) – side view and plan view [104].

Ambient temperature, relative humidity, wind speed, and wind direction were measured during the experiment. Ambient temperature varied from around 0°C in winter to $+30^\circ\text{C}$ in summer during the observation period. Relative humidity remained mainly above 60 % during the entire observation period. Wind speed varied from 0 to approximately 20 m/s, with an average value of approximately 6 m/s, mainly from the south-west.

To determine the dynamic parameters, 20 PCB and B&K piezoelectric accelerometers were used, 16 of which were placed on the bridge deck and four on both reinforced concrete pylons at the level of the cable anchors (Fig. 4.3). The sensors with coaxial cables were connected to both the four-channel NI 9234 and the three-channel NI 9230 vibration input modules, which were installed on the 8-channel NI CompactDAQ 9178 chassis, allowing signals to be acquired simultaneously. A laptop computer with LabVIEW software was used for data acquisition, control, and data storage. The acceleration data obtained during the experiment were sampled at a frequency of $f_s = 100$ Hz, divided into 30-minute time series, band-pass filtered, and a covariance-driven stochastic subspace identification method (SSI-COV) was used to determine the natural frequencies [104].

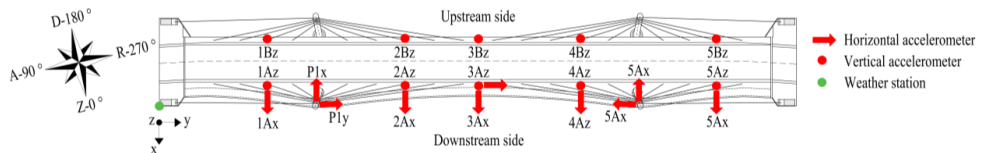


Fig. 4.3. Sensor location plan for the Filomena Delli Castelli bridge [104].

The natural frequencies of the first six mode shapes of the bridge were identified: f_1 corresponding to the first deck bending, f_2 to the first deck torsional, f_3 to the second deck bending, f_4 and f_5 to the second deck torsional, and f_6 to the third deck bending mode shape. The first three natural frequencies show slight seasonal fluctuations, with an increase in frequency values during the winter months and a slight decrease during the summer months. However, the second three natural frequencies remain at a constant average frequency level during the entire observation period. All frequencies show separate short-term decreases and increases in values; however, no significant long-term increase or decrease in frequency values can be observed.

Analysis of the natural frequency distribution indicates that the data for the lowest frequencies f_1 and f_2 are relatively symmetrical and close to a normal distribution. However, frequencies from f_3 to f_6 show a clear asymmetry and several local peaks, indicating an unequal data distribution during the monitoring period that deviates from a normal distribution.

To determine the impact of environmental factors, the relationships between natural frequencies and each environmental factor were analysed using **linear** and **quadratic functions**. The goodness of fit of these functions was evaluated. The choice of regression functions is based on a gradual increase in model complexity to preserve the physical interpretability of the results and avoid the risk of overfitting [94]. The linear model enables verification of the assumption of a proportional relationship between environmental factors and natural frequencies [105], while the quadratic model can describe parabolic nonlinear relationships more accurately, identifying local extremes or symmetrical changes [106]. The model coefficients were determined using the MATLAB command *polyfit* for first- and second-order polynomials.

To assess the goodness of fit of the regression models to the data and to determine which linear or nonlinear relationship best describes the impact of the environmental factor on the natural frequencies, a model comparison approach based on the Bayesian information criterion (BIC) was applied [107]. This criterion allows models with different numbers of parameters to be compared, while considering both residual error and model complexity. A model with a lower BIC value is considered better because it provides an optimal compromise between data approximation quality and model simplicity [108]. To compare regression models, the BIC difference was analysed, where a positive ΔBIC value favours the quadratic (nonlinear) model, while a negative value favours the linear model for describing the data [109]. The adjusted coefficient of determination ($Adj R^2$) was used to evaluate model fit, as it accounts for both the goodness of fit and the number of independent variables included in the model. A higher $Adj R^2$ value indicates better model performance and a stronger relationship between the environmental factors and the natural frequencies [86].

For the **wooden frame**, the relationships between natural frequency and ambient temperature, relative humidity, and precipitation were analysed. The relationships between each natural frequency and ambient temperature are presented in graphs (Fig. 4.4) together with the linear and quadratic model fit metrics – the adjusted coefficient of determination $Adj R^2$, and the difference in the Bayesian information criterion ΔBIC . The impact of relative humidity and

precipitation on natural frequency is analysed and graphically presented similarly, evaluating the suitability of both models using $Adj R^2$ and ΔBIC for each natural frequency.

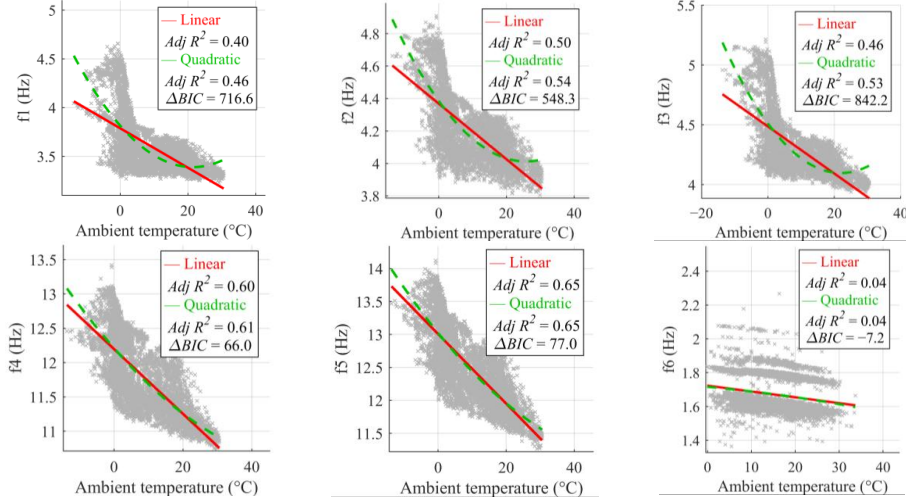


Fig. 4.4. Correlation between ambient temperature and natural frequencies of the wooden frame during the observation period.

Analysis of the natural frequency of the wooden frame and the ambient temperature outside indicates that the frequency values decrease as the temperature increases. The linear model describes the overall trend with a moderately high adjusted coefficient of determination $Adj R^2$ values, but lower Bayesian information criterion (BIC) values for the quadratic model indicate that the nonlinear model provides a statistically significant improvement in data description. For relative humidity, the natural frequency increases as the relative humidity values increase. The linear model describes the overall trend with sufficient accuracy, but the adjusted coefficient of determination $Adj R^2$ values are relatively low, indicating a statistically justified advantage of the nonlinear model. However, in the case of precipitation, no significant statistical correlation can be observed across the entire frequency range analysed, as confirmed by the very low $Adj R^2$ values and small ΔBIC values.

For the **Filomena Delli Castelli bridge**, the relationships between natural frequencies and ambient temperature, relative humidity, and wind speed were analysed.

In the analysis of the impact of wind speed on natural frequencies, the impact of wind direction relative to the orientation of the structure is also considered. In the following analysis, wind speed is divided into two components – the longitudinal component V_g and the transverse component V_{sk} , which corresponds to wind projections parallel and perpendicular to the longitudinal axis of the bridge [110].

Wind components are calculated using the following equations:

$$V_g = V \times \cos(\Delta\theta) \text{ and } V_{sk} = V \times \sin(\Delta\theta), \quad (4.1)$$

where V is the wind speed measured at the exact observation time, and $\Delta\theta$ is the relative angle between the wind direction and the longitudinal axis of the bridge. The relative angle is defined as the difference between the wind direction determined by weather observations and the

orientation angle of the bridge's longitudinal axis, which, in the case of the Filomena Delli Castelli bridge, is 102° . The longitudinal component V_g characterises the impact of the wind parallel to the bridge longitudinal axis, while the transverse component V_{sk} characterises the impact of the wind perpendicular to the bridge's longitudinal axis [111].

The relationships between each natural frequency and the ambient temperature are presented in graphs (Fig. 4.5) together with the linear and quadratic model fit metrics – the adjusted coefficient of determination $Adj R^2$ and the Bayesian information criterion difference ΔBIC . The impact of the relationship between relative humidity and wind speed on natural frequencies is analysed and graphically presented similarly, evaluating the suitability of both models using $Adj R^2$ and ΔBIC for each natural frequency.

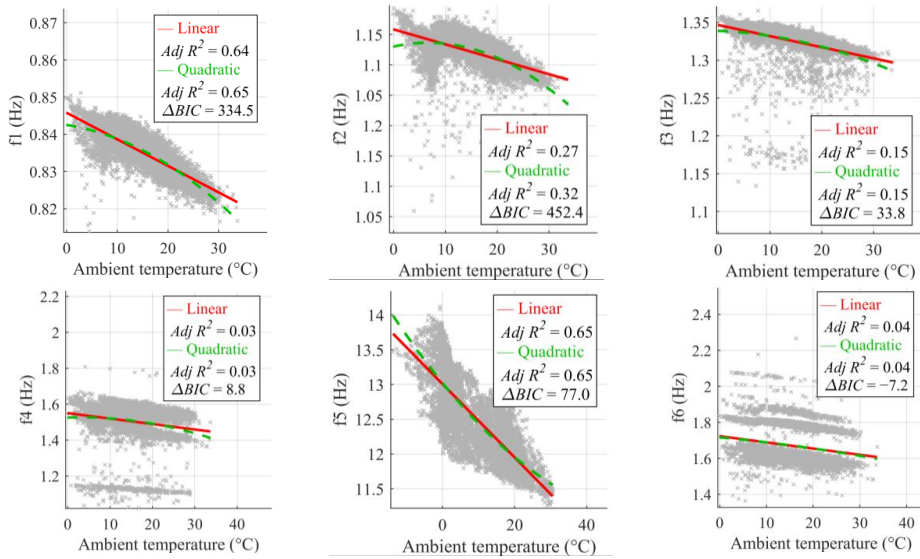


Fig. 4.5. Correlation between ambient temperature and natural frequencies of the Filomena Delli Castelli bridge during the observation period.

For the Filomena Delli Castelli bridge, as the ambient temperature increases, the natural frequency values decrease. The linear model describes the general decreasing trend; however, the adjusted coefficient of determination $Adj R^2$ values are low for most of the natural frequencies. In some cases, the quadratic model presents a slightly higher $Adj R^2$ value and a lower Bayesian information criterion (BIC) value, but its application is not statistically justified across the entire range of relevant frequency values. The impact of relative humidity and wind components on the frequency values of natural frequencies is small, and the overall correlation trend is weak. The linear regression model can describe the general trend, but the low values of the adjusted coefficient of determination $Adj R^2$ indicate the limited ability of the regression model to fit the data. The use of the quadratic model in only a few cases gives slightly lower Bayesian information criterion (BIC) values, which is confirmed by positive, but small ΔBIC values, indicating that a more complex model does not significantly improve the correlation between relative humidity and changes in wind component and natural frequency values.

Overall, the relationship between the natural frequencies of both the wooden frame and the Filomena Delli Castelli bridge and environmental factors indicates that the influence can be both weak and significantly non-linear. The results confirm that a simplified linear assumption is not sufficient for accurate assessment of changes in natural frequency values. Therefore, nonlinear models must be used to identify structural damage.

When evaluating the impact of environmental factors on the dynamic properties of structures, it is important to assess not only the individual impact of each factor but also the correlation between these factors, as well as the correlation between natural frequencies. A high correlation between natural frequencies indicates that they respond similarly to changes in environmental conditions, while a low correlation indicates that different frequencies respond independently or differently, which may be important in the analysis and interpretation of changes in dynamic properties [75].

To evaluate the **linear correlation** between environmental factors and natural frequencies, Pearson's linear correlation coefficients were calculated for both the wooden frame and the Filomena Delli Castelli bridge (Fig. 4.6). Pearson linear coefficient values close to zero indicate a weak linear relationship, while values close to one indicate a strong linear relationship [112].

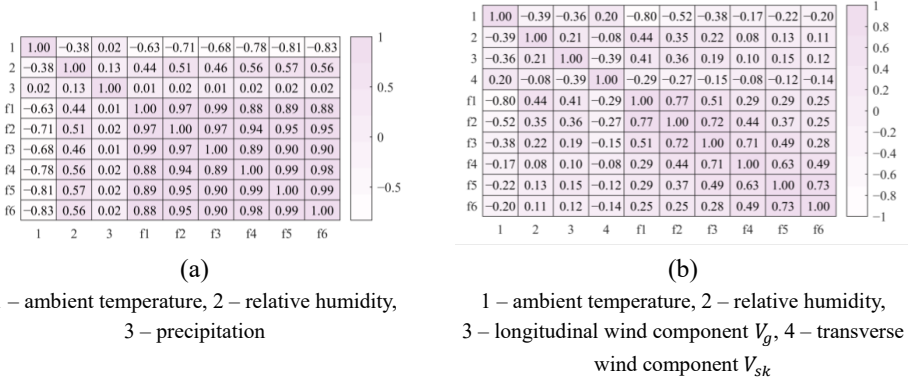


Fig. 4.6. Pearson linear correlation coefficients between the natural frequencies of the wooden frame (a) and the Filomena Delli Castelli Bridge (b) and environmental factors.

For the wooden frame, high mutual correlation values are observed between all natural frequencies, especially between the lower frequencies f_1 , f_2 , and f_3 . However, between the lowest and highest natural frequencies, there is a slightly lower, but still strong, correlation.

For the Filomena Delli Castelli bridge, the mutual correlation of natural frequencies is lower than in the case of the wooden frame. The correlation between the lowest natural frequencies f_1 , f_2 , and f_3 is higher, but the correlation between the lowest and highest frequencies is moderate or weak.

Between the ambient temperature and relative humidity, a stronger negative correlation is observed in both cases. This means that as the ambient temperature increases, the relative humidity usually decreases. In the case of the wooden frame, there is a weak correlation between precipitation and all other factors, while in the case of the Filomena Delli Castelli bridge, there is a negative correlation between relative humidity and wind speed components.

However, there is a weak positive correlation between the ambient temperature and the longitudinal wind component V_g and the transverse wind component V_{sk} , indicating a low mutual relationship.

The correlation matrix of environmental factors confirms that there are moderate correlations between some factors; however, the impact of most environmental factors is mutually independent or weakly correlated, and depending on the nature of the factor, both an increase and a decrease in frequency can be observed with varying intensity of impact in different ranges. This indicates that the impact of each factor on the dynamic properties of the structure can be analysed individually, given that no strong mutual interactions are observed.

Three algorithms were used to analyse the impact of various environmental factors on natural frequencies: the **XGBoost algorithm**, **Gaussian process regression (GPR)**, and **random forest regression (RF)**. The selection of these algorithms was based on their ability to model complex nonlinear and non-homogeneous relationships between environmental factors and natural frequencies of structures, while ensuring high generalisation ability and reducing the risk of overfitting [85]. The regularisation mechanisms in the XGBoost structure maintain model stability and allow for quantitative assessment of the impact of individual environmental factors [113]. The RF algorithm effectively processes high-dimensional datasets and significantly reduces the risk of overfitting [85], while the GPR algorithm ensures high prediction accuracy and quantitative assessment of prediction uncertainty [90].

K-fold cross-validation with a parameter value of $k = 5$ was used to train all models and evaluate the results obtained, dividing the datasets into five subsets. In each iteration, one subset was used for testing, while the other four subsets were used for model training. Thus, no separate test set is selected, while reducing the dispersion of evaluation results in the analysis of long-term monitoring data [114].

The results of the analysis of the impact of environmental factors were summarised in a total change graph and impact matrix. The overall impact of each environmental factor on the corresponding natural frequency was determined using the predicted frequency value calculated by the regression model at the minimum and maximum values of the environmental factor being analysed within its observation range, while keeping the other environmental factors constant at their average value. The difference between these two predicted natural frequency values was taken as the magnitude of the impact [90].

The total change indicates how much the absolute value of the natural frequency changes when the environmental factor changes across its entire range. The sign of the total change indicates whether a particular environmental factor increases (positive sign) or decreases (negative sign) the value of the natural frequency.

To compare the natural frequencies, the relative total impact was also analysed by determining the weight of the absolute changes compared to the average value of the natural frequency during the analysed period and calculating the result as a percentage.

Relative impact analysis provides a quantitative comparison of the impact of environmental factors on different natural frequencies by determining the relative change in each natural frequency due to the impact of the specific environmental factor [19].

Gradient boosting regression (XGBoost) was applied using the MATLAB command *fitensemble*, which creates a regression model based on the least squares boosting (LSBoost) algorithm. Hyperparameter optimisation (number of training cycles, learning rate, maximum number of splits, minimum leaf size) was performed using the function *AcquisitionFunctionName* to reduce error and overfitting risk. The final prediction was calculated as the weighted sum of all decision trees created during the iterations [94].

In the case of the **random forest regression algorithm (RF)**, the prediction was determined as the average value of all tree predictions. The hyperparameters (number of decision trees, minimum leaf size, number of variables to use in each splitting step) were optimised using the MATLAB *fitensemble* command [115].

In the **Gaussian process regression (GPR) method**, the frequency dependence of natural frequencies on environmental factors was modelled as a Gaussian process using the MATLAB command *fitrgp* with automatic hyperparameter optimisation (length scale, noise variance parameter value, basis function). Model training and hyperparameter optimisation were performed indirectly by minimising the negative log-likelihood function (NLL) [90].

For the **wooden frame**, the impact of the ambient temperature and relative humidity on all six natural frequencies was analysed. The impact of environmental factors on natural frequencies using the XGBoost method is presented in graphs (Fig. 4.7), with the absolute (Hz) and relative (%) impact presented separately. The results of the RF and GPR algorithms were analysed and graphically represented in an identical manner, comparing the obtained absolute and relative impact values for each natural frequency.

The analysis of the absolute and relative impact of environmental factors on the natural frequencies of wooden frame revealed similar general trends. In all methods, the ambient temperature had the greatest negative impact on the natural frequencies, while relative humidity had a moderate positive absolute impact on the natural frequencies in all methods.

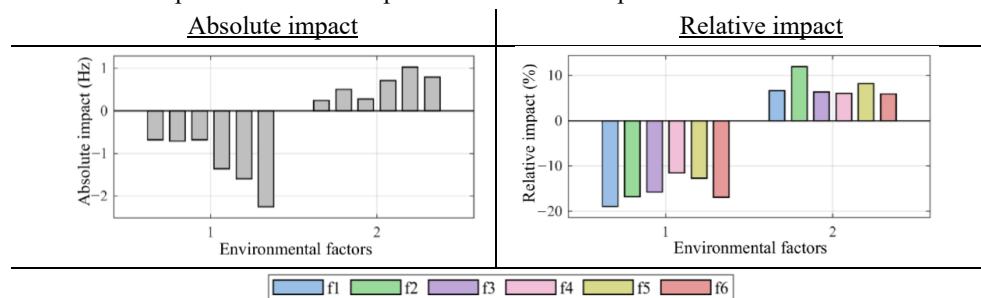


Fig. 4.7. Impact of environmental factors on the natural frequencies of wooden frame using the XGBoost method (1 – ambient temperature ($^{\circ}\text{C}$), 2 – relative humidity (%)).

For the **Filomena Delli Castelli bridge**, the impact of ambient temperature, relative humidity, and wind components on all six natural frequencies was also analysed. The effect of ambient temperature on natural frequencies using the XGBoost method is presented in graphs (Fig. 4.8), separately indicating the absolute (Hz) and relative (%) impact. Similarly, the results of the RF and GPR algorithms were analysed and graphically presented, comparing the obtained absolute and relative impact values for each natural frequency.

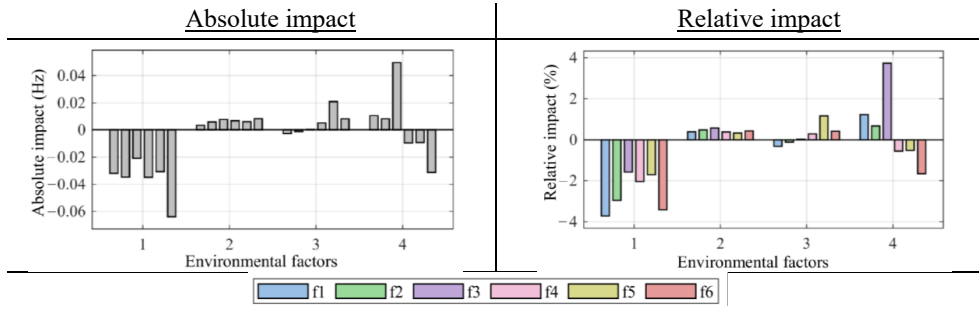


Fig. 4.8. Impact of environmental factors on the natural frequencies of the Filomena Delli Castelli bridge using the XGBoost method (1 – ambient temperature ($^{\circ}\text{C}$); 2 – relative humidity (%); 3 – longitudinal wind component V_g , (m/s); 4 – transverse wind component V_{sk} (m/s)).

Analysing the impact of environmental factors on natural frequencies of the bridge, the results obtained indicate that in all three methods, the most significant impact on the natural frequencies is the ambient temperature, which has a negative overall impact on all analysed frequencies. Relative humidity has a more moderate impact on the natural frequency values, and its impact varies between the different methods for the individual analysed frequencies. In most cases, analysis of the impact of the longitudinal wind component V_g indicates a small positive impact on natural frequencies. However, the transverse wind component V_{sk} has a more significant negative impact, especially for the higher frequencies f4, f5, and f6.

To analyse the character of changes in the natural frequency of a **wooden frame** in multidimensional space and to evaluate deviations from the undamaged state of the structure, four methods were used: the Mahalanobis distance algorithm, principal component analysis (PCA), one-class support vector machine (OC-SVM) analysis, and Gaussian mixture model (GMM) based anomaly analysis.

Each method is based on a different anomaly detection principle and enables the identification of changes in natural frequencies by evaluating their distance, projection, decision boundary, or distributional differences relative to the undamaged state dataset [116].

Initially, the algorithm combines data from both damaged and undamaged structural states into a single data set, with each observation containing six natural frequencies. To ensure data comparability, all natural frequency values in the combined data set are normalised using a robust normalisation method based on the median and interquartile range (IQR). This method is selected because the natural frequency data do not follow a clear normal distribution and may contain outliers [117].

To characterise the distribution of undamaged state data, the mean vector μ is calculated for all natural frequencies [75]. For some algorithms, the covariance matrix is also calculated to describe how frequencies vary together over time, which allows their mutual correlation to be considered rather than analysing each natural frequency separately. If the frequencies increase or decrease systematically at the same time, these relationships are directly reflected in the covariance matrix [118].

The Mahalanobis distance algorithm is an unsupervised machine learning-based anomaly detection method that evaluates the distance of an observation from an undamaged dataset in multidimensional space, considering the mutual correlation and variance structure of the parameters [119]. Initially, the Mahalanobis distance algorithm determines the mean vector μ of damage-sensitive features of the undamaged state and the covariance matrix S . After obtaining these values, the Mahalanobis distance is calculated for all data points that characterise the deviation from the undamaged data distribution in multidimensional space. For anomaly detection, an upper control limit (UCL) is defined based on the chi-square distribution and a selected probability of false alarm ($PFA = 0.05$). Natural frequency values with a Mahalanobis distance exceeding the UCL are considered anomalies.

Principal component analysis (PCA) for structural damage detection is based on dimensional reduction by identifying the main features of the data structure. PCA transforms the original data into a new orthogonal space where the principal components are mutually independent and maximise data variance. PCA is based on the diagonalisation of the covariance matrix, which enables the extraction of eigenvalues and eigenvectors [120]. The significance of each principal component is determined by its explained variance ratio, which indicates how much of the total data variance is explained by a particular component. To optimise damage detection, the grid search method is used, selecting the level of retained variance (90 %, 95 %, 99 %) and significance level α (0.01, 0.05, 0.1) for calculating the control limit of Hotelling's T^2 statistic. If the T^2 statistic exceeds the control limit, the observation is classified as damaged [121].

The one-class support vector (OC-SVM) machine learning algorithm is used for anomaly detection in datasets where most of the data corresponds to the undamaged structural state, and only a small part of the data represents outliers. During the training phase, the algorithm learns the boundary that defines the normal data region and then classifies new observations as normal or anomalies. A radial basis function (RBF) is used to model nonlinear relationships. Hyperparameters (γ and ν) are determined by Bayesian optimisation, maximising balanced accuracy over 30 iterations [91]. Anomalies are identified based on the value of the decision function and a defined threshold. In this case, the threshold is set as the 5 % quantile, and points below this threshold are classified as anomalies.

The Gaussian mixture model (GMM) method assumes that the natural frequency data of the undamaged state follow a multidimensional distribution that can be approximated with sufficient accuracy by K multivariate normal distributions, where each component has its own weight, mean vector, and covariance matrix that characterises the mutual relationships among the natural frequencies. Significant deviations from this distribution are interpreted as possible anomalies. After GMM training, the negative log-likelihood (NLL) is calculated for each observation x_i . The higher the NLL value, the lower the probability that the observation corresponds to the data of the undamaged state of the structure [122]. The parameters (number of components $K = 1, 2, 3$ and significance level $\alpha = 0.01, 0.05, 0.1$) are selected by grid search based on balanced accuracy. After determining the optimal model, the classification threshold τ is calculated using $(100 \% \cdot (1 - \alpha))$ -th percentile of the NLL distribution. Observations with an NLL value above this threshold are classified as anomalies.

The classification of observations using the Mahalanobis distance algorithm, PCA, OC-SVM, and GMM methods is based on a specific threshold value that determines whether an observation corresponds to an undamaged structural state or is considered a deviation. A threshold that is set too low increases the number of false positives, while a threshold that is set too high increases the number of false negatives.

In a binary classification problem, each observation can be classified as a true positive (TP), false positive (FP), true negative (TN), or false negative (FN).

To evaluate the accuracy of the methods used, **balanced accuracy** is calculated by analysing the number of correctly classified and incorrectly classified cases. Two main criteria are used to determine balanced accuracy: sensitivity and specificity. Sensitivity represents the proportion of correctly identified damaged cases ($TP/(TP + FN)$), while specificity represents the proportion of correctly identified undamaged cases ($TN/(TN + FP)$). Given that the number of undamaged and damaged data is not similar, balanced accuracy is determined, which ensures that the model is evaluated equally regardless of class imbalance [116].

The classification results of the Mahalanobis distance algorithm, principal component analysis (PCA), one-class support vector machine (OC-SVM) analysis, and Gaussian mixture model (GMM) using wooden frame monitoring data before applying the method for reducing the impact of environmental factors are summarised in Fig. 4.9.

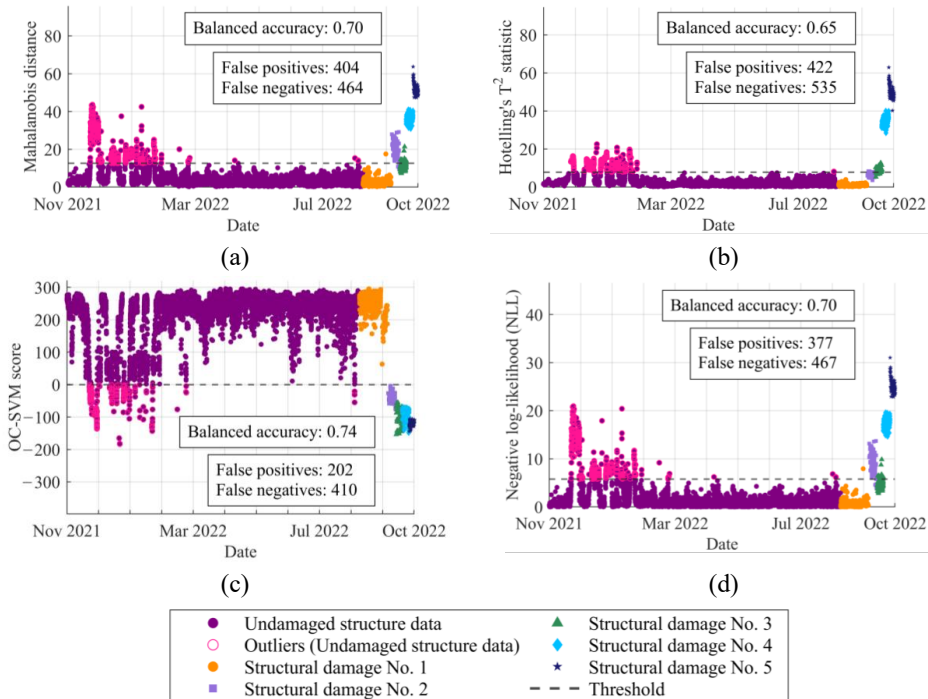


Fig. 4.9. Results of the Mahalanobis distance algorithm (a), PCA method (b), OC-SVM method (c), and GMM method (d) for structural damage detection using all six natural frequencies of the wooden frame.

The Mahalanobis distance algorithm achieved 70 % balanced accuracy, correctly identifying most of the undamaged data. However, the number of false negatives (464) and false positives (404) was relatively high, mainly during the winter months. The results of the PCA method demonstrated lower balanced accuracy (65 %) and a higher number of false positive (422) and false negative (535) cases, which indicates a lower capability of the method to identify structural damage and reduces the effectiveness of the monitoring system. The OC-SVM method provided 74 % balanced accuracy. False positive results (202) are mainly concentrated during the winter period, while the number of false negative cases did not exceed 410. The GMM method achieved 70 % balanced accuracy, indicating a moderate ability to separate undamaged and damaged structural data. However, 377 false positives and 467 false negatives were identified, especially during the winter months.

The results obtained by the structural damage detection algorithm clearly indicate that the performance of the algorithm is significantly affected by environmental factors. This is particularly important during the winter period, when fluctuations in environmental factors, such as significant ambient temperature changes and increased relative humidity, can cause changes in the dynamic parameters of structures. These changes are often misinterpreted as structural damage, thereby increasing the number of false alarms.

The distribution of false positives in the Mahalanobis distance algorithm in the time histories of environmental factor variations is presented in Fig. 4.10. The distribution of false positive results for the PCA, OC-SVM, and GMM methods was analysed and graphically presented similarly, indicating specific periods and extreme values in which changes in the dominant environmental factor are interpreted as structural damage.

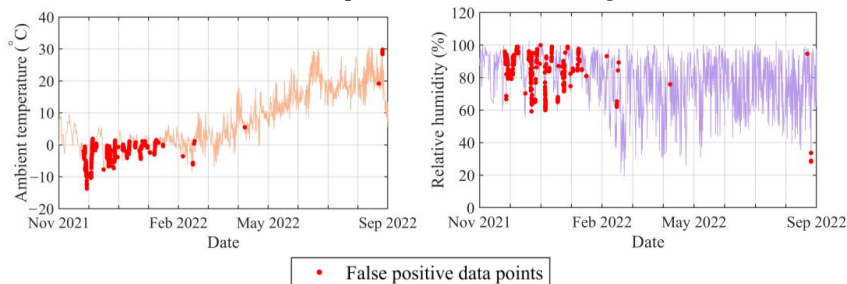


Fig. 4.10. Distribution of false positive results of the Mahalanobis distance algorithm in the time histories of environmental factor variations.

False positive results for all methods are mainly concentrated in periods of abrupt changes in environmental factors. Anomalies most often occur in conditions of low ambient temperature, when the temperature is below 0 °C, as well as during periods of abrupt and significant temperature changes, especially in winter. There is also a high concentration of anomalies at high relative humidity, mainly 80 %. However, some false positive points are found during the entire observation period and do not correspond to the maximum or minimum values of the environmental factor in any of the time periods.

To validate the method for reducing the impact of environmental factors, previously acquired experimental monitoring data for the two-storey wooden frame and Filomena Delli Castelli bridge structures were used, which included the first six natural frequency values.

In **Stage 1** of the method for reducing the impact of environmental factors on the wooden frame, the natural frequency values and environmental factor data were combined into a single dataset, based on the measurement timestamps. In **Stage 2** of the method, seven different regression models were used to model the dependence of each natural frequency on environmental factors (SVR, RF, LR, DT, XGBoost, GPR, and BR). In **Stage 3** of the method, the accuracy of each model was evaluated using the composite performance metric (CPM), which combines the R^2 , RMSE, MAE and MAPE metrics.

For each of the regression models, mean global CPM values were calculated (Fig. 4.11) for modelling the relationships between all environmental factors (ambient temperature, relative humidity) and all natural frequencies.

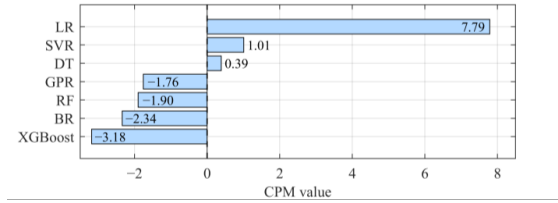


Fig. 4.11. Mean global CPM values of regression models for modelling the relationship between environmental factors and the natural frequencies of the wooden frame.

In **stage 4** of the method, the XGBoost regression model with the lowest global CPM value is selected to determine the change points. The identified change points defining the impact of ambient temperature and relative humidity are presented in Fig. 4.12.

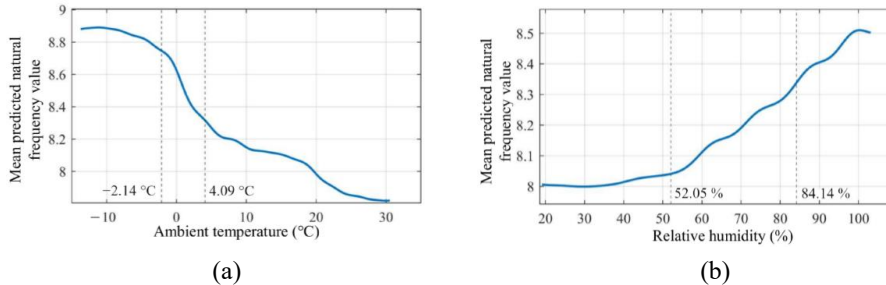


Fig. 4.12. PDP curves obtained using the XGBoost method for identifying the segmentation of the impact of ambient temperature (a) and relative humidity (b) in the wooden frame monitoring data.

Three segment change points are defined for the ambient temperature: up to -2.14 °C, from -2.14 °C to $+4.09$ °C, and above $+4.09$ °C. The relative humidity segment change points are defined as up to 52.05 %, from 52.05 % to 84.14 %, and above 84.14 %.

The identified change points reflect significant changes in the dynamic response of the wooden frame and coincide with the threshold value of -5 °C mentioned in other studies. This ambient temperature value is frequently used as a threshold in operational and testing standards [123]. However, the change points defining the relative humidity impact segments are very close to the service class for timber structures specified in LVS EN 1995-1-1:2005 (below 65 %, from 65 % to 85 %, and above 85 %).

In stage 5 of the method, separate regression models are determined for each environmental factor impact segment. For each natural frequency and each regression model within a given environmental factor impact segment, the composite performance metric (CPM) is calculated.

The PDP graphs illustrate the relationships between *ambient temperature* and natural frequencies together with the identified segment change points (Fig. 4.13).

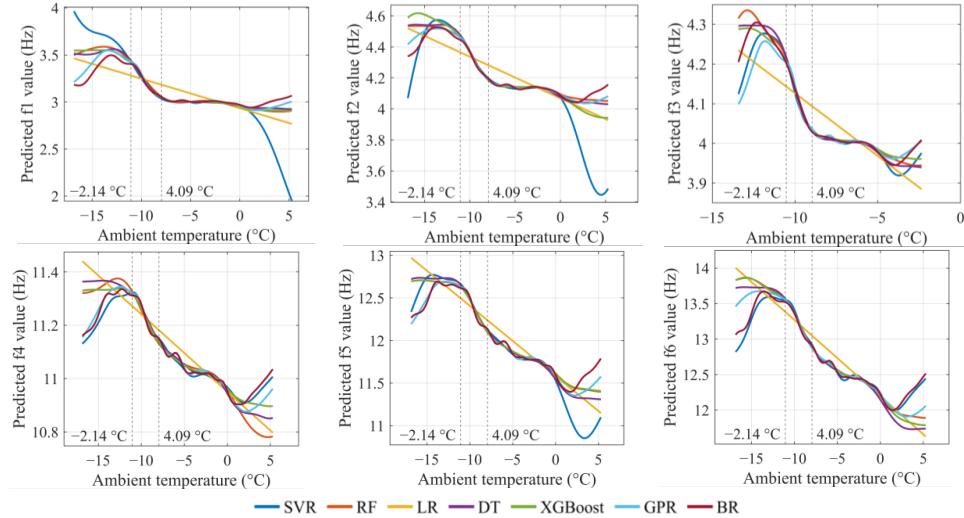


Fig. 4.13. PDP curves of ambient temperature impact wooden frame natural frequencies.

The overall trend in all PDP graphs indicates a clear negative correlation between the ambient temperature and natural frequencies – the frequency value decreases as the ambient temperature increases (Fig. 4.13). Up to $-2.14\text{ }^{\circ}\text{C}$, the frequency values increase gradually, but in the segment from $-2.14\text{ }^{\circ}\text{C}$ to $+4.09\text{ }^{\circ}\text{C}$, a rapid drop in values is observed, and the predictions of all seven regression models overlap in this zone. Above $+4.09\text{ }^{\circ}\text{C}$, more pronounced nonlinear differences appear both between models and between natural frequencies.

The CPM values of regression models for modelling the relationship between ambient temperature and natural frequency in individual segments are summarised in Fig. 4.14.

	$T \leq -2.14\text{ }^{\circ}\text{C}$							$-2.14\text{ }^{\circ}\text{C} < T \leq 4.09\text{ }^{\circ}\text{C}$							$T > 4.09\text{ }^{\circ}\text{C}$							
f1	1.25	-1.70	8.35	-0.15	-2.24	-1.93	-3.57	2.98	-0.26	7.27	-1.15	-4.63	-1.07	-3.14	0.84	0.68	8.16	-1.02	-3.51	-1.82	-3.34	
f2	-0.27	-2.02	8.63	0.67	-2.39	-2.00	-2.61	1.91	-4.69	7.60	0.90	-1.89	-1.44	-2.40	0.90	-4.21	7.95	0.48	0.03	-2.13	-3.01	
f3	-0.70	-0.29	8.66	-0.20	-3.04	-2.88	-1.54	1.37	0.36	7.22	0.26	-5.75	-2.75	-0.71	-0.29	0.60	8.24	-0.30	-4.18	-2.88	-1.19	
f4	-0.88	-3.82	7.85	2.55	-2.55	-1.51	-1.65	0.81	-3.58	7.39	1.42	-4.88	-0.34	-0.83	0.03	-2.07	7.79	1.80	-4.67	-1.27	-1.60	
f5	0.36	-3.05	7.93	2.14	-3.05	-2.11	-2.21	2.78	-4.51	6.79	0.65	-4.49	-0.48	-0.74	2.40	-4.23	6.98	1.51	-4.22	-1.09	-1.35	
f6	-1.34	-0.67	8.48	0.63	-0.80	-2.61	-3.69	0.29	-0.64	8.35	-0.51	-0.88	-2.33	-4.28	-0.63	0.35	7.95	-0.38	0.40	-2.80	-4.89	
Mean	-0.26	-1.92	8.32	0.94	-2.35	-2.17	-2.54	1.69	-2.22	7.44	0.26	-3.75	-1.40	-2.02	0.54	-1.48	7.84	0.35	-2.69	-2.00	-2.56	
Std.dev.	0.94	1.35	0.35	1.16	0.83	0.49	0.92	1.07	2.29	0.52	0.95	1.91	0.98	1.50	1.10	2.35	0.45	1.12	2.28	0.75	1.45	
	SVR	RF	LR	DT	XGBoost	GPR	BR	SVR	RF	LR	DT	XGBoost	GPR	BR	SVR	RF	LR	DT	XGBoost	GPR	BR	

Fig. 4.14. CPM values of the regression models for ambient temperature segments up to $-2.14\text{ }^{\circ}\text{C}$, from $-2.14\text{ }^{\circ}\text{C}$ to $4.09\text{ }^{\circ}\text{C}$ and above $4.09\text{ }^{\circ}\text{C}$ in the wooden frame monitoring data.

Analysis of the impact of *ambient temperature* indicates that the performance of regression models varies significantly across segments. Linear regression (LR) has the lowest accuracy in all segments, while nonlinear models achieve lower mean CPM values, confirming their better fit to the data.

The PDP graphs illustrating the relationship between relative humidity and natural frequencies, together with identified segment change points and CPM values of regression models within individual segments, were analysed and presented similarly to the analysis of ambient temperature impact.

For *relative humidity*, most regression models and natural frequencies indicate a tendency for the predicted frequency value to increase as humidity increases. However, this relationship is not linear across the entire relative humidity range. For the segment up to 52.05 % relative humidity, the PDP curve indicates a relatively stable or very slow increase in most cases. For segments from 52.05 % to 84.14 % and above 84.14 %, a more pronounced increase in frequency values can be observed. The CPM values of the regression models indicate that the prediction accuracy is uneven and significantly depends on both humidity range and selected method.

Summarising all CPM value results, the lowest values were obtained using:

- 1) Bayesian regression (BR) method – in the ambient temperature segment up to $-2.14\text{ }^{\circ}\text{C}$, in the relative humidity segment from 0 % to 52.05 %;
- 2) XGBoost method – in the ambient temperature segment from $-2.14\text{ }^{\circ}\text{C}$ to $+4.09\text{ }^{\circ}\text{C}$, in the ambient temperature segment above $+4.09\text{ }^{\circ}\text{C}$, in the relative humidity segment from 52.05 % to 84.14 %, and in the relative humidity segment from 84.14 % to 100 %.

These regression models were used to generate partial dependence plots (PDP) of a reduced number of grid points for each natural frequency and each environmental factor. The optimal number of grid points that most accurately describes the curve function according to a specific convergence criterion is 400 points for natural frequencies f1, f3, and f4, 150 points for f2, and 500 points for f6 in the case of ambient temperature. For relative humidity, f1, f5, and f6 require 500 points, f2 requires 150 points, and f3 requires 350 points. The corresponding PDP curve was interpolated for each natural frequency value and each environmental impact factor according to the actual value of the environmental factor. In the next step, the natural frequency values were corrected by removing the total segmented environmental impact value.

Additional regression models – LSBoost, GPR, SVR, and Bagging – were trained on these corrected natural frequency values to assess the remaining nonlinear environmental impact relationships. The model with the lowest MSE was selected, and the final correction was obtained by removing the predicted residual environmental impact component at the corresponding measurement time for each natural frequency. In the final stage, the seasonal effect was removed by subtracting the seasonal component and adding its mean value.

The method for reducing the impact of environmental factors was applied to all six natural frequencies of the **Filomena Delli Castelli bridge**. In **Stage 1**, the natural frequency values and environmental factor data were combined into a single dataset. In **Stage 2**, the dependence of each natural frequency on environmental factors was modelled using seven different regression

models. In **Stage 3**, the mean global CPM values were calculated for each regression model (Fig. 4.15).

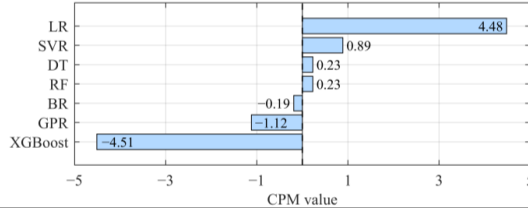


Fig. 4.15. Mean global CPM values of regression models for modelling environmental factors and the natural frequencies relationship of the Filomena Delli Castelli bridge.

In **Stage 4** of the method, the XGBoost regression model with the lowest global CPM value is selected to determine the change points. The identified change points defining the impact of ambient temperature, relative humidity, longitudinal wind component V_g and transverse wind component V_{sk} are presented in Fig. 4.16.

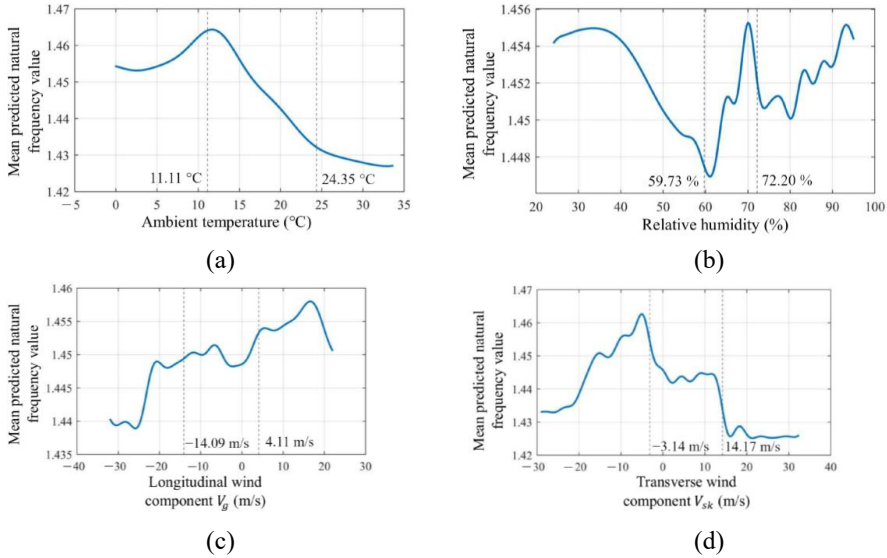


Fig. 4.16. PDP curves obtained using the XGBoost method to identify the segmentation of the impact of ambient temperature (a), relative humidity (b), longitudinal wind component V_g (c) and transverse wind component V_{sk} (d) in the Filomena Delli Castelli bridge monitoring data.

Three segment change points are defined for the ambient temperature: up to +11.11 °C, from +11.11 °C to +24.35 °C, and above +24.35 °C. The relative humidity segment change points are defined: up to 59.73 %, from 59.73 % to 72.20 %, and above 72.20 %. The change points defining the impact of the longitudinal wind component V_g are defined: up to -14.09 m/s, from -14.09 m/s to 4.11 m/s, and above 4.11 m/s. For the transverse wind component V_{sk} are: up to -3.14 m/s, from -3.14 m/s to 14.17 m/s, and above 14.17 m/s.

In **Stage 5** of the method, separate regression models are determined for each environmental factor impact segment. For each natural frequency and each regression model within a given

environmental factor impact segment, the composite performance metric (CPM) is also calculated.

The PDP graphs illustrate the relationships between *ambient temperature* and natural frequencies together with the identified segment change points (Fig. 4.17).

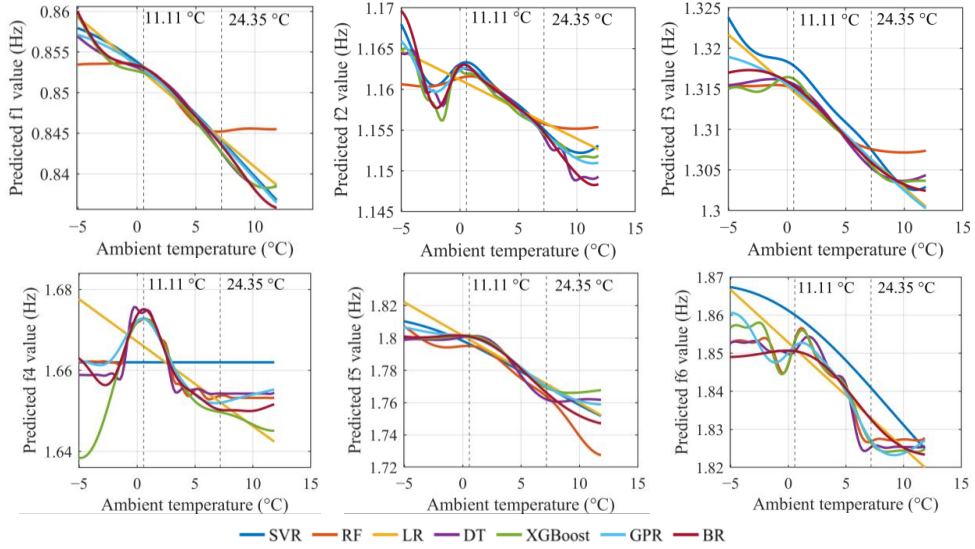


Fig. 4.17. PDP curves illustrating the impact of ambient temperature on the natural frequencies of the Filomena Delli Castelli bridge.

The overall trend in all PDP graphs (Fig. 4.17) indicates a clearly negative correlation between the ambient temperature and the natural frequencies. In the ambient temperature impact segment from +11.11 °C to +24.35 °C, the natural frequency values predicted by regression models are relatively similar, and the overall trend remains unchanged. However, in the impact segment up to +11.11 °C and in the segment above +24.35 °C, the predicted frequency values differ both across natural frequencies and across regression models.

The CPM values of regression models for modelling the relationship between ambient temperature and natural frequency in individual segments are summarized in Fig. 4.18.

T < 11.11 °C								11.11 °C ≤ T < 24.35 °C								T ≥ 24.35 °C							
f1	0.61	3.74	5.59	-2.94	-5.86	-0.06	-1.08	-2.17	5.29	6.31	-2.62	-2.68	-2.38	-1.75	-1.89	8.91	0.18	-1.83	-1.72	-1.83	-1.82		
f2	-2.42	3.04	7.57	-1.48	-2.84	-2.66	-1.21	-3.31	1.23	7.80	-0.08	-0.89	-4.26	-0.49	-3.93	4.82	5.91	0.04	-0.98	-3.86	-2.00		
f3	-1.96	2.29	1.57	0.59	-4.16	0.91	0.76	-2.84	0.47	3.27	1.30	-4.37	0.90	1.28	-3.03	1.89	0.11	1.87	-1.95	0.45	0.66		
f4	5.43	-0.07	2.28	0.32	-7.49	-0.62	0.15	4.68	0.08	3.76	0.46	-7.47	-1.60	0.09	0.38	1.54	2.75	2.12	-8.07	0.11	1.16		
f5	1.46	-7.00	5.02	2.04	-3.31	0.81	0.98	1.59	-5.14	5.04	3.59	-4.94	-0.19	0.05	-2.05	-4.40	4.99	0.80	1.94	-0.49	-0.79		
f6	6.67	-2.93	3.42	-0.44	-5.20	-1.53	-0.00	5.97	-3.33	3.82	0.13	-5.55	-1.11	0.06	7.00	-1.55	0.98	1.68	-4.73	-3.59	0.22		
Mean	1.63	-0.15	4.24	-0.32	-4.81	-0.53	-0.07	0.65	-0.23	5.00	0.46	-4.32	-1.44	-0.13	-0.59	1.87	2.49	0.78	-2.58	-1.53	-0.43		
Std.dev.	3.75	4.15	2.24	1.73	1.73	1.39	0.91	4.03	3.66	1.76	2.02	2.29	1.79	0.98	3.99	4.68	2.50	1.49	3.43	1.87	1.32		
	SVR	RF	LR	DT	XGBoost	GPR	BR	SVR	RF	LR	DT	XGBoost	GPR	BR	SVR	RF	LR	DT	XGBoost	GPR	BR		

Fig. 4.18. CPM values of the regression models for ambient temperature up to +11.11 °C, from +11.11 °C to +24.35 °C and above +24.35 °C in the Filomena Delli Castelli bridge monitoring data.

Analysis of the impact of *ambient temperature* indicates that the linear regression (LR) model presents the highest CPM values, while nonlinear models achieve lower CPM values, similar to the wooden frame.

The PDP graphs illustrating the relationship between relative humidity, longitudinal wind component V_g , transverse wind component V_{sk} and natural frequencies, together with identified segment change points and CPM values of regression models within individual segments, were analysed and presented similarly to the analysis of ambient temperature impact.

For *relative humidity*, the natural frequency values increase as the relative humidity increases. For the impact segment up to 59.73 %, a significant difference can be observed among the prediction curves of the regression models compared to the other impact segments. However, in the remaining relative humidity impact segments, the regression model prediction values are similar for most natural frequency values, and the curves overlap in the graphs.

For the *longitudinal wind component* V_g in the impact segment of up to -14.09 m/s, the ability of regression models to predict natural frequency values differs both between models and between individual frequencies. However, within the impact segments from -14.09 m/s to 4.11 m/s and above 4.11 m/s, the natural frequency predictions of most regression models are similar.

For the *transverse wind component* V_{sk} in the segment up to -3.14 m/s, the ability of regression models to predict natural frequency values differs both between models and between individual frequencies, similar to the longitudinal wind component V_g . However, in the impact segments from -3.14 m/s to 14.17 m/s and above 14.17 m/s, the natural frequency predictions of most regression models are similar to each other, indicating a decrease in natural frequency values.

Summarising all CPM value results from all seven regression models, the lowest CPM values for each environmental impact factor across all segments were obtained using the XGBoost method. This regression method was used to create partial dependence plots (PDP) for each natural frequency and each environmental factor. The optimal number of grid points that most accurately describes the curve function with a specific convergence criterion is 100 points for all natural frequencies in the case of ambient temperature, relative humidity, and the longitudinal wind component V_g and the transverse wind component V_{sk} .

In the next stages, the natural frequency values were corrected using segmented PDP curves for each environmental impact factor. After removing the segmented impact, additional regression models were trained on the corrected natural-frequency values to identify the remaining nonlinear environmental-impact relationships. In the final stage, the seasonal effect was removed to obtain the final corrected natural frequency values.

Mahalanobis distance, principal component analysis (PCA), one-class support vector machine (OC-SVM) analysis, and Gaussian mixture model (GMM) deviation analysis were used to evaluate the effectiveness of methods for reducing the impact of environmental factors reported in publications. For comparison, only those methods were used in which environmental factors are modelled directly, and their impact is reduced based on an analysis of the structure's dynamic parameters. The methods were adapted to the monitoring data for the

wooden frame. Within each method, only the impact of the environmental factor specified in the publication was analysed and reduced.

A comparison of the methods for reducing the impact of the environmental factors analysed in the publications, using all six natural frequencies of the wooden frame, revealed significant differences in damage-detection accuracy. The principal component analysis (PCA) [74] and Bayesian model updating [79] methods achieve higher balanced accuracy (up to 0.72 and 0.74), whereas for autoregressive models [75] the accuracy does not exceed 0.52.

Therefore, the results obtained using methods to reduce the impact of environmental factors on the natural frequency of a wooden frame indicate that the methods proposed in the publications do not ensure a significant improvement in the accuracy of structural damage detection. Although in some cases a slight increase in balanced accuracy can be observed, overall, the results vary and depend on the method used for structural damage detection.

To evaluate the effectiveness of the method for reducing the impact of environmental factors on the natural frequencies of the **wooden frame**, all four previously analysed algorithms for detecting structural damage were used. For each method, balanced accuracy and the numbers of false positives and false negatives were determined (Fig. 4.19). Based on these results, it was analysed whether the method for reducing the impact of environmental factors improves each model's ability to identify structural damage and whether the algorithm reduces false positives, which were particularly observed during the winter period.

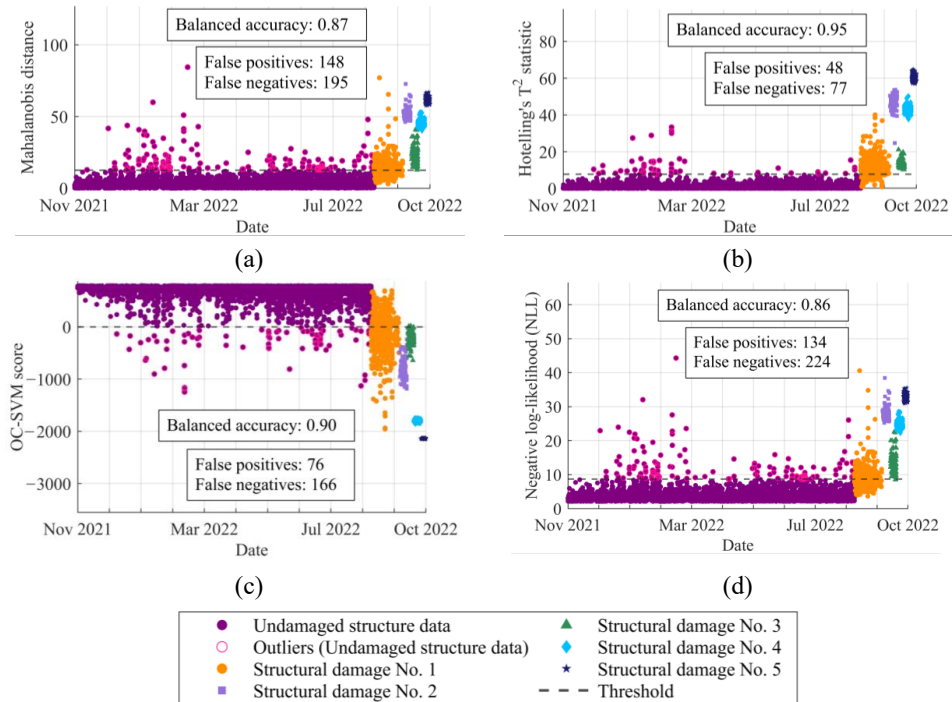


Fig. 4.19. Results of the Mahalanobis distance (a), PCA method (b), OC-SVM method (c), and GMM method (d) for structural damage detection using all six natural frequencies of the wooden frame after reducing the impact of environmental factors on natural frequencies.

After implementing the method for reducing the impact of environmental factors, the balanced accuracy of all methods improved significantly, and the number of false positives and false negatives decreased. After the correction, all methods fully identified the structural damage data starting from level 2 and partially also the level 1 damage data, which had previously been classified as completely undamaged structural data.

The distribution of false positives in the Mahalanobis distance algorithm in the time histories of environmental factor variations after implementing the method for reducing the impact of environmental factors on natural frequencies is presented in Fig. 4.20. The distribution of false positive results for the PCA, OC-SVM, and GMM methods was analysed and graphically presented in the same manner as before the implementation of the method for reducing the impact of environmental factors.

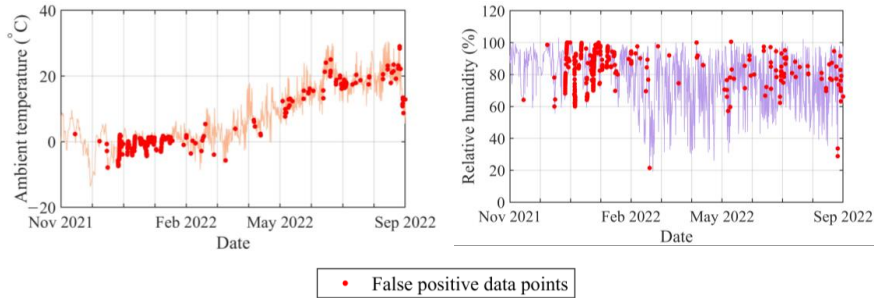


Fig. 4.20. Distribution of false positive results of the Mahalanobis distance in the time histories of environmental factor variations after correction of natural frequencies.

Summarising and analysing the false positives after implementing the method for reducing the impact of environmental factors on natural frequencies, as presented in the time histories of environmental factor variations, it can be concluded that anomalies identified by the Mahalanobis distance algorithm, OC-SVM, PCA, and GMM methods are dispersed throughout the entire observation period and are not particularly concentrated in periods of low ambient temperature and high relative humidity.

Comparing the changes in the number of false positives and false negatives before and after correction of natural frequencies, the PCA and OC-SVM methods were most effective in reducing false alarms, especially during the winter period. However, the number of false negatives was reduced most by the PCA method and least by the GMM method.

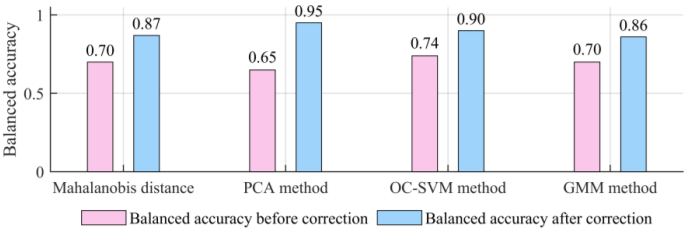


Fig. 4.21. Balanced accuracy comparison of the methods applied.

Comparing the accuracy of all four methods, before implementing the method to reduce the impact of environmental factors, the balanced accuracy values ranged from 65 % to 74 %.

However, after implementing the method, the balanced accuracies across all methods ranged from 86 % to 95 %. The highest increase in balanced accuracy was observed for the PCA method, while the lowest was observed for the GMM method.

To evaluate the effectiveness of the method for reducing the impact of environmental factors on the natural frequencies of the **wooden frame** and of the **Filomena Delli Castelli**, the changes in the natural frequency Δf were analysed, the frequency time series before and after correction were compared, and the coefficients of variation in Fig. 4.22 (CV) were determined.

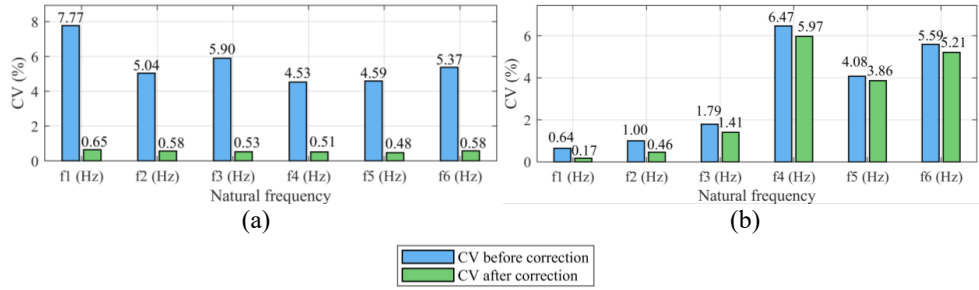


Fig. 4.22. Comparison of the coefficient of variation CV for the natural frequencies of the wooden frame and of the Filomena Delli Castelli bridge.

After implementing the method to reduce the impact of environmental factors on the natural frequencies of the wooden frame, it can be concluded that for the first three natural frequencies, f1, f2, and f3, the changes are small and uniform, with median values close to zero, indicating a stable correction. However, for the higher natural frequencies f4, f5, and f6, the median values remain close to zero, with slightly greater dispersion, without introducing a systematic bias. After correction, the time series of natural frequency values becomes more uniform, with both the overall dispersion of values and short-term local fluctuation decreasing. The CV values of the natural frequencies of the wooden frame before and after correction are visually compared, indicating the result of the method for each natural frequency separately. This confirms that the method effectively reduces the impact of environmental factors, stabilising the natural frequency values of the wooden frame and improving the accuracy of the data for future structural health monitoring and damage detection.

After implementing the method to reduce the impact of environmental factors on the natural frequencies of the Filomena Delli Castelli bridge, it can be concluded that the correction method significantly changes the frequency values for only f1 and f2 natural frequencies during the observation period. For the other natural frequencies, the changes in values are minimal. The distribution of frequency changes of the bridge after correction is not uniform for all natural frequencies. For the lower frequencies f1, f2, and f3, the change values Δf are concentrated around zero, but for the higher natural frequencies f4, f5, and f6, a greater dispersion of Δf is observed, characterised by a wider interquartile range (IQR) and individual local deviations. The obtained results confirm that the method of reducing the impact of environmental factors effectively corrects the natural frequency values of the bridge, decreasing the dispersion of frequency values during the observation period.

CONCLUSIONS

Within the framework of this study, a new adaptive method for structural health monitoring of load-bearing structures was developed and validated, enabling the reduction of the impact of varying environmental factors and enhancing the accuracy of damage detection. This method is based on the combined application of multiple machine learning algorithms and segmented modelling of environmental factor impacts, providing significantly higher accuracy in identifying structural damage and reducing the risk of false alarms. The method was validated using long-term monitoring data from a two-storey wooden frame and the Filomena Delli Castelli bridge, demonstrating its practical applicability to different types of structures.

Analysis of experimentally obtained dynamic monitoring data from the two-storey wooden frame and the Filomena Delli Castelli bridge clearly indicated that the natural frequency values of structures are significantly affected by environmental factors, for example, ambient temperature, relative humidity, and wind.

The main conclusions are summarised as follows.

- 1) It was found that the impact and nature of environmental factors on the natural frequencies are highly nonlinear and vary across different seasonal periods. For this reason, the segmentation of the identified natural frequency data provides a significantly more accurate impact reduction, considering a consistent application of the method for each range separately.
- 2) The method for reducing the impact of environmental factors combines the adaptive selection of multiple regression models with physically justified segmentation for each environmental factor separately. The calculation of the composite performance metric (CPM) values indicated significant differences in model performance, confirming the necessity to apply different regression models to the segments of environmental impact factors depending on the nature of the specific range.
- 3) Partial dependence plots (PDP) for each natural frequency and each environmental impact factor clearly indicated that linear regression (LR) provides only a general trend for changes in natural frequencies due to changes in environmental factors. Nonlinear regression models were more capable of adapting to and describing changes in natural frequencies, but even in this case, prediction accuracy depended on the selected model. The highest accuracy in modelling the relationship between the impact of environmental factors and changes in natural frequency was achieved by XGBoost and Bayesian regression (BR) in the case of a wooden frame, and by XGBoost regression in the case of a bridge.
- 4) The implementation of the method results in a set of discrete partial dependence plot (PDP) values that provide relevant information about the impact of the environmental factors on the natural frequency values. This approach allows a large training dataset to be replaced with a reduced, structured reference dataset, significantly decreasing the volume of stored data while maintaining high correction accuracy.
- 5) The results of the study confirmed that the developed method significantly improves the accuracy of the structural damage detection algorithm. Before the frequency value

correction, the Mahalanobis distance, PCA, OC-SVM, and GMM methods presented a wide dispersion of false positive and negative results, particularly during the winter period.

- 6) After applying the method for reducing the impact of environmental factors to the natural frequencies of the wooden frame, the balanced accuracy of the Mahalanobis distance increased from 70 % to 87 %, the balanced accuracy of the PCA method increased from 65 % to 95 %, while the balanced accuracy of the OC-SVM and GMM methods after correction increased from 74 % to 90 % and from 70 % to 86 %, respectively. The results obtained confirm that, after applying the method for reducing the impact of environmental factors on the natural frequency monitoring data, machine learning algorithms can separate changes caused by environmental factors from actual indications of structural damage, significantly improving the reliability of damage detection.
- 7) After applying the method for reducing the impact of environmental factors to the natural frequencies of the Filomena Delli Castelli bridge, a significant reduction in the dispersion of frequency values was observed for the lower frequencies. The decrease in the coefficient of variation (CV) for all natural frequencies confirms that the method effectively corrects fluctuations caused by environmental factor impacts.

To ensure reliable damage detection and accurate assessment of the structural condition, several important assumptions must be considered when implementing a monitoring system.

- 1) To ensure accurate and representative data acquisition, monitoring systems must integrate multiple sensors, for example, accelerometers, sensors for measuring ambient temperature, relative humidity, and wind speed.
- 2) Monitoring equipment must be periodically inspected and calibrated to ensure high measurement accuracy and to prevent sensor malfunctions.
- 3) Measuring devices should be placed at critical points of the structure to obtain detailed data on structural vibrations in different directions and at different points.
- 4) To obtain reliable and representative results about changes in dynamic parameters, monitoring is required for at least one year to observe seasonal fluctuations.

The Doctoral Thesis makes a significant contribution to structural health monitoring and ensures the rational use of resources. The method's practical applicability enables maintenance and reconstruction work to be planned based on quantitative assessments of structural condition rather than on the results of periodic visual inspections. The developed method promotes the transition from traditional to data-driven building management, which is an essential part of a sustainable construction and operation strategy.

The validation of the developed method was based on a simplified two-storey wooden frame with adjusted frequencies and long-term monitoring data from a single bridge, which limits the generalizability of the results to complex real structures. Damage was simulated in a non-destructive manner, without irreversible damage. The effectiveness of the method depends on high-quality and continuous monitoring data, which is not always available in practice. The study considered only the main environmental factors; therefore, in real objects, an expanded set of impacts and additional corrections may be necessary.

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