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ANYTWIN - Characterization and standardization of monitoring data

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ABSTRACT: Aging bridges were not designed for today's higher traffic loads and often fail to meet current requirements. However, complete demolition or reconstruction is rarely feasible due to resource limitations, sustainability concerns and economic factors. A key issue lies in conservative assumptions regarding loads and resistance. Structural health monitoring (SHM) addresses this by providing real measurement data for a more accurate assessment.

Monitoring produces large volumes of data that must be well-structured and stored for reliable assessments. This requires collaboration between civil engineers, measurement specialists, IT experts, and data analysts. As Building Information Modeling (BIM) adoption grows, standardized monitoring methods must ensure consistency and comply with the Single Source of Truth (SSoT) principle, enabling an integration of monitoring data in a BIM environment.

The ANYTWIN research project aims to develop a framework for structured data storage and processing. It examines how measurement data relates to time and location, defines metadata and information for evaluation criteria and assigns responsibilities for data provision. A processing method ensures data preparation, analysis, and data mining, while quality indicators enhance reliability. These findings contribute to a tendering template, helping to structure monitoring tasks and improve maintenance strategies.

KEY WORDS: Structural health monitoring (SHM); Standardization; Monitoring data; Data Quality; Quality Indicator; Tendering template.

1 INTRODUCTION

Existing bridges age over time and were not designed for today's significantly higher traffic loads. Many of these structures no longer meet the current verification requirements of the Eurocode. However, complete demolition or new construction is not a practical solution—on one hand, the necessary resources for demolition and reconstruction are lacking; on the other hand, such an approach would be neither sustainable nor economically viable.

A primary shortcoming in meeting verification requirements arises from the conservative assumptions made regarding both loads and resistance. This is where structural health monitoring becomes crucial: by collecting measurement data, a more precise and realistic assessment of the bridge's condition can be made [1][2]. SHM allows for the adjustment of both load assumptions and structural resistance based on actual measurements, thereby enabling more accurate verification.

The monitoring process generates vast amounts of data, which must be well-organized and properly stored to ensure a clear understanding of the bridge's condition. This requires close collaboration among civil engineers, measurement experts, IT specialists and data analysts. As part of the ongoing digitalization effort and the adoption of Building Information Modeling (BIM), this collaboration should be enhanced while adhering to the Single Source of Truth (SSoT) principle. In a digital environment, such as a digital twin, various datasets and information sources converge, interconnect, and depend on each other. A structured representation of these relationships is essential for seamless integration. While the IFC model primarily serves as a static representation, it provides key information for monitoring, including the positions of individual measurement points, cable routing and other infrastructure details.

However, the digital twin extends beyond this by dynamically reflecting the current sensor status, generating meaningful analyses of physical parameters at these points, and integrating diagnostic method data for a more comprehensive assessment. This approach enables a real-time, data-driven understanding of structural conditions. All of this should be guided by the principle that the digital twin serves as the SSoT, ensuring that all information is consistently structured, linked, and accessible within a unified system.

To achieve this, monitoring methods should be standardized and incorporated into data-based load-bearing safety checks in civil engineering [3].

This is precisely the aim of the ANYTWIN research project [4], [5], [6]. The goal of the project is to establish a clear structure for collecting, storing and processing monitoring data. Different types of measurement data are analyzed and classified to ensure systematic storage. The project investigates how measurement data is connected over time and space, identifies key details necessary for evaluation, and defines responsibilities for data provision. A processing method is also developed to ensure that the data is transformed into clean and usable time series. Finally, the project establishes the quality requirements that the data must meet for specific verification purposes and defines quality indicators for assessment.

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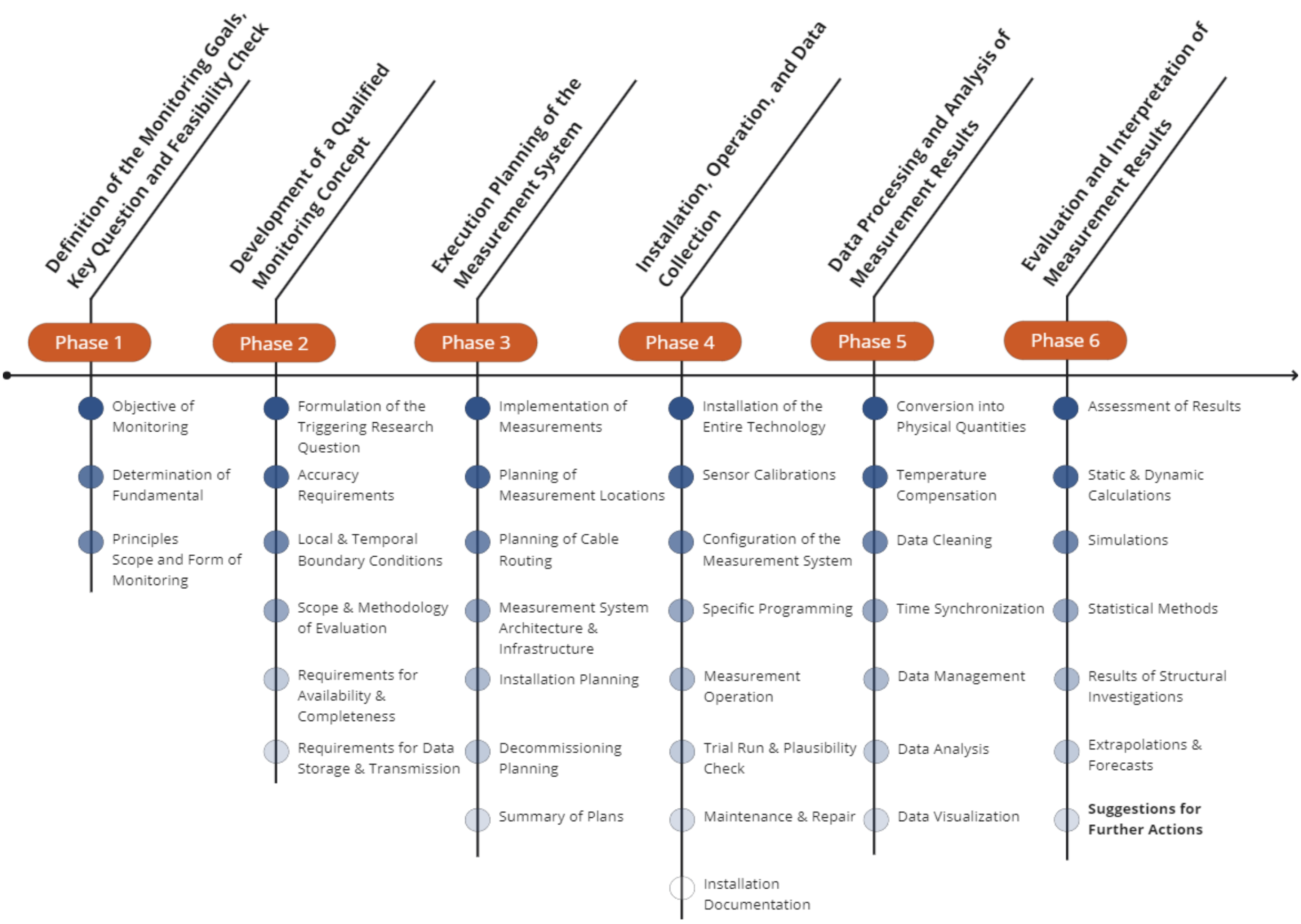

Figure 1. Representation of the individual phases of a monitoring process based on the DBV guideline [11], © MKP GmbH

All these findings will contribute to the standardization of tendering processes, providing project owners with a comprehensive overview of monitoring tasks and the respective responsibilities of all involved experts. The objective is to generate significant value for the future maintenance and management of bridges [7].

2 IMPLEMENTATION OF MONITORING IN BRIDGE CONSTRUCTION

The implementation of monitoring in bridge construction is still not a standardized procedure and is typically conducted on a case- by-case basis [8], [9], [10]. However, a structured approach has been established, based on the recommendations of the DBV guidelines [11]. According to these guidelines, the monitoring process consists of six phases, ranging from defining the objective, planning, installation, and operation of the monitoring system to the evaluation and assessment of measurement results (see Figure 1). In practice, these phases have not yet been fully standardized.

Regardless of the specific task, certain measurement parameters and objectives have been identified as crucial for the effective implementation of monitoring.

Specifically, for damage detection and computational verification in structural monitoring, the following measurement objectives are relevant:

Temperature & Environment: Measures temperature differences and climatic effects (e.g., temperature sensors, humidity sensors, thermocouples, resistance thermometers, infrared detectors). These parameters are crucial for assessing thermal loads on structures.

Moisture Measurements: Detects humidity levels and influences such as corrosion or mineral formation that can lead to durability issues (e.g., humidity sensors, multi-ring electrodes).

Fatigue & Cracks: Identifies stress, strain, and early cracks (e.g., strain gauges, DFOS [12], Acoustic Emission Sensors (AE Sensors) [13]), which are strong indicators of structural load-bearing capacity.

Deformation & Movement: Monitors settlements, vibrations and inclinations (e.g., displacement sensors, tilt sensors, acceleration sensors, distance sensors). By analyzing geometric changes at micro, meso and macro levels, insights into bearing movements, expansion behavior, creep & shrinkage, and crack formation can be derived.

Load & Traffic: Detects overloads and load distribution (e.g., pressure sensors, laser measurement systems), which are critical for understanding structural performance under varying traffic loads.

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Vibration Monitoring: Assesses dynamic structural properties, such as natural frequencies and damping values, which provide insights into fatigue behavior and potential damage (e.g., accelerometers, vibration velocity sensors).

Acoustic Monitoring: Captures sound events to track damage progression caused by localized failure events (e.g., AE Sensors [13]).

The selection of sensors depends on the measurement objective, type of structure, and environmental conditions and is adapted to specific requirements. Figure 2 illustrates some examples of sensors and measurement systems used for bridge monitoring.

3 TYPES OF MONITORING DATA AND SENSORS

The efforts to standardize the handling of monitoring data obtained in the context of SHM require a comprehensive examination and description of the characteristics and typical features of such data. This foundational understanding enables subsequent classification and the formulation of universally applicable procedures for processing, evaluation, data manipulation, and establishment of quality requirements.

The term 'monitoring data' refers to the entirety of data generated in the context of SHM. In typical monitoring processes, sensor measurement data constitute the predominant volume of data. However, for effective information extraction, it is crucial to link these data with metadata, defined as all data describing the measurement.

In the initial phase of this study, the measurement data are examined. Measurement data include all data that originate directly from sensing devices on the structure. To account for the increasing technological capabilities of system-on-a-chip (SoC) solutions and edge computing, the term is also applied to data generated through automated process steps close to the sensor or hardware level, provided that their characteristics allow them to be treated as measurement data.

To illustrate the range of potential measurement data sources, typical measurement methods and their use cases briefly presented in Section 2, serves as a reference. The list focuses on recognized and proven methods without claiming to be exhaustive.

The classification of measurement data can be based on various criteria and is generally necessary to address both software-related aspects in the creation of a storage and processing infrastructure, as well as content-related aspects for the metadata to be collected.

One fundamental property describes the data in relation to a *measurement location*. Three main variants can be distinguished: point measurement methods, line measurement methods, and field measurement methods.

- **Point measurement methods** (e.g., strain gauges) provide information about a discrete measurement point with a very small spatial extent relative to the structure being monitored.
- **Line measurement methods** (e.g., distributed fiber optic sensing (DFOS) [12]) generate measurement data along a line with high spatial resolution.
- **Field measurement methods** (e.g., photogrammetry) can be used for measurements over a larger (surface) area.

Figure 2. Example of Sensor Technology in Structural Monitoring in Use, © MKP GmbH

A second classification criterion characterizes *the temporal structure* of the measurement data. Continuous and discontinuous data can be distinguished:

- **Continuous data** are stored throughout the entire monitoring period with equidistant time intervals between consecutive data samples, typically with a low sampling rate (ranging from several minutes to hours).
- **Discontinuous data** are recorded over a typically short period of time at a high sampling rate. The recording time can be determined either by a predefined time pattern or by data-dependent trigger conditions.

Another classification option concerns *the temporal reference* of the measurement data. The simplest case is a direct assignment between the individual instantaneous value of the measurement signal and the timestamp. A further possibility is that the measurement data refer to a time-extended measurement interval, such as in the case of averaging. Even more complex time reference descriptions arise with methods like Rainflow counting or Fast Fourier Transform analysis (FFT).

A fundamental category of properties for the storage structure of measurement data is *the dimension of the index* required to address a measurement value. Besides storage, this also determines the programmatic interfaces to processing algorithms. The most common attributes in this category are:

- 1 index value per single measurement value,
- 1 index value per n measurement values, and
- 2 index values per 1 measurement value.

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For time series, the index always includes at least the timestamp. Additional index values may be required, for example, to identify a location or direction.

Finally, a classification can be made based on *the underlying measurement instrument(s)* of the data. This is mainly used when assigning technical metadata. A key distinction is whether the data originate from a single, clearly identifiable sensor (element) or whether a sensor combination, a sensor array, or an automated/autonomous processing algorithm (e.g., a Weigh-In-Motion (WIM) system) should be considered as the data source.

Table 1 provides an overview of the key characteristics of the measurement data (measurement location, temporal structure, temporal reference, index dimension, and technical data source) and categorizes them into subgroups (a to c). Each subgroup was formed by identifying up to three distinct properties for each feature. This classification facilitates the systematic organization and comparison of different types of measurement data and supports further analysis and processing.

Table 2 provides an evaluation of the characteristics describing the generated measurement data based on the established classification system for specific measurement methods and sensor technologies. It categorizes different sensors according to common characteristics and highlights potential groupings.

To facilitate abstraction, a '1' is assigned to applicable feature variants and a '0' to non-applicable ones. Gray shading is used to highlight transitions within a category. A gray mark appears in the feature column 1 to 5 whenever the assignment within a feature category changes from 0 to 1 or 1 to 0.

Through this visual grouping, at least seven sensor groups can be identified. Sensors sharing the same color pattern are classified into the same category. In this case, temperature sensors up to acceleration sensors (Table 2) are grouped together, as they exhibit identical feature combinations across the evaluated categories. In contrast, the multi-sensor system differs from these sensors, which typically measure a single physical quantity. Instead, a multi-sensor system can generate multiple independent measurement variables. As a result, its classification varies, particularly in Feature 5 (technical data source).

Table 1. Presentation and classification of characteristics for describing the generated measurement data

Classification option	**Property 1 (a)**	**Property 2 (b)**	**Property 3 (c)**
Feature 1: measurement location	Point measurement method	Line measurement method	Field measurement method
Feature 2: temporal structure	Continuous time-series-data	Discontinuous time-series-data, segments with fixed time interval	Discontinuous time-series-data with event-driven time interval
Feature 3: temporal reference	Single instantaneous value	(statistical) value derived from a time span	Indirect value based of underlying data
Feature 4: index dimension	1 index per 1 measurement sample	1 index per n measurement samples	2 indices per 1 measurement sample
Feature 5: technical data source	Direct data - sensor alignment	Indirect data-sensor alignment	-

Table 2. Evaluation of characteristics for describing the generated measurement data from various measurement systems

Examples of measurement systems	**Feature 1**			**Feature 2**			**Feature 3**			**Feature 4**			**Feature 5**	
	a	**b**	**c**	**a**	**b**	**c**	**a**	**b**	**c**	**a**	**b**	**c**	**a**	**b**
Temperature sensors	1	0	0	1	1	0	1	1	0	0	1	0	1	0
Strain gauges	1	0	0	1	1	0	1	1	0	0	1	0	1	0
Displacement sensors	1	0	0	1	1	0	1	1	0	0	1	0	1	0
Acceleration sensors	1	0	0	1	1	0	1	1	0	0	1	0	1	0
Multi-sensor	1	0	0	1	1	0	1	1	0	0	1	0	0	1
Corrosion sensor	1	0	0	1	0	0	1	0	1	0	1	0	1	0
Weigh-in-Motion (WIM)	1	0	0	0	0	1	1	0	1	0	1	0	1	0
AE Sensors	1	0	0	0	0	1	0	1	1	0	1	0	1	0
DFOS	0	1	0	0	1	0	1	0	0	0	0	1	1	0
Laser scan	0	0	1	1	0	1	0	0	1	0	0	1	1	0
Tachymeter-total station	0	0	1	1	0	1	0	0	1	0	0	1	1	0

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Considering the goal of this grouping, it is crucial for data structuring to determine how measurement values should be assigned to their respective IDs or timestamps. Only Feature 1 and Feature 4, which are marked with bold borders in the table, are representative in this context.

These groupings reflect common classification features, allowing them to be treated as uniform types when assigning descriptive metadata, organizing data storage, and designing input and output interfaces for data processing.

For Feature 1, continuity on the spatial scale does not impact data structuring, thereby reducing the number of groups to two. For Feature 4, the key question is whether data should be structured as an array or a matrix. This decision is essential for grouping, as both Features (1 and 4) can be combined. The result is a definite grouping of sensors, which simplifies data structuring and enhances the readability of the stored datae.

4 RELEVANT METADATA AND ADDITIONAL INFORMATION IN BRIDGE MONITORING

In addition to the actual measurement data, another essential category of data exists: metadata and metainformation. For evaluations and measurement-based verifications, obtaining specific data and information from the measuring point on the structure and metadata from the installed measurement system or sensors is of great importance. This data is needed to apply the calculation method in data processing and evaluation while ensuring traceability of time-based trends, providing a comprehensive understanding of the structure's behavior over time and at specific locations.

According to the definition in the ANYTWIN research project, *metadata* refers to numerical, machine-readable values that can be assigned to sensors or measurement systems. In contrast, *metainformation* consists of structured, interpreted content and descriptions provided by actors, such as textual explanations. Both types of data are characterized by their stability, as they are generally static and determined once. An exception is when a sensor is replaced, which necessitates an update of the metadata and metainformation.

Metadata is defined either during the development of the measurement concept or determined after sensor installation. It can be divided into two main categories:

1. **General metadata for sensor types** – Cross-sensor information, such as the measurement method, the unit of the electrical signal, and the function used to convert the electrical signal into physical values.
2. **Specific metadata for installed sensors and measurement points** – These are unique to each installed sensor, its measurement system, and the respective measuring location. They include:
    - Sensor characteristics: such as conversion factors and calibration parameters
    - Measurement parameters: such as sampling rate, measurement ranges and spatial resolution
    - Measurement point characteristics: such as material properties like modulus of elasticity or thermal expansion coefficient
    - Technical properties of the measurement system: such as frequency range and filtering methods
    - Additional evaluation parameters like installation values, calibration data and sensor orientation

In addition to metadata, additional informative metainformation is available, providing details about the installed sensors and measurement techniques. This data is not necessarily included in the metadata and is not directly relevant for data evaluation. However, it is important for traceability, quality assurance, and functional verification of the sensors, for example, in assessing their lifespan.

Unlike metadata, metainformation does not have to be stored in a machine-readable format. While it may include similar categories as metadata, it provides additional details that do not directly contribute to data analysis, such as:

- Measurement parameters: Additional metrics, such as the maximum measurement range or sensor frequency range
- Influencing factors: Environmental conditions, temperature compensation, background noise
- Technical properties of the measurement system: Connection type, measurement amplifier specifications
- Structural properties of the measurement points: Sensor protection mechanisms, material characteristics, installation date, expected lifespan

Table 3. Overview of metadata and metainformation categories and actors responsibilities

	Monitoring specialist planner	Structural monitoring service provider
General metadata for sensor type		
Measurement method (relative/absolute)	-	✓
Unit of the electrical signal	-	✓
Function model	-	✓
Specific metadata from installed sensors and measurement points		
Sensor characteristics	-	✓
Measurement parameters	-	✓
Measurement point characteristics	✓	-
Properties of the measurement system	-	✓
Additional parameters for evaluation	✓	-
Informative data for documentation and traceability		
Measurement parameters	-	✓
Influencing factors	✓	✓
Technical properties of the measurement system	-	✓
Structural properties of measurement points	✓	✓

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Metadata and metainformation are provided and documented by different actors involved in various phases of the monitoring process. The monitoring specialist planner defines general sensor metadata and metainformation during the planning phase and in the creation of the measurement concept. This includes key parameters of the measurement point, such as surface area or modulus of elasticity. The specialized service provider for structural measurements is responsible for recording and providing specific sensor metadata and metainformation during installation. Additionally, they handle sensor calibration and update metadata and metainformation during maintenance or sensor replacement to ensure measurement accuracy and data consistency.

Table 3 provides an overview of common metadata types and the corresponding roles of actors.

5 DATA PROCESSING MODEL

Structural monitoring encompasses the processes of data acquisition, including data transmission and management, as well as data analysis, which involves evaluation, validation, and plausibility checks. Based on this, an assessment of the current structural condition or a forecast of future structural behavior can be conducted. This sequential process can also occur cyclically, with the system continuously receiving new data. Prior to this cyclical process, the preparation of the monitoring measures can be implemented. The success of a monitoring project largely depends on a structured workflow, where the monitoring objective remains the central focus [11].

This section introduces the data processing model developed in the ANYTWIN research project for monitoring data. This model aims to combine various sensor types, short-term, long-term, and continuous measurements, as well as different data processing methods, including machine learning, into a single process.

The model is based on well-known data processing models (CRISP-DM, SEMMA, Fayyad, DBV guidelines, Farrar) and consists of eight main steps [11], [14], [15], [16], [17], [18]. These steps are highlighted in orange in Figure 3. Additionally, the feedback loop, highlighted in blue, ensures that the collected data meets the required quality standards and that the resulting maintenance recommendations are well-founded and reliable. All process steps are iterative. This means that it may be necessary to go back and repeat previous steps to refine the analysis and improve the results.

Quality management is an ongoing process that spans the entire monitoring workflow – from defining the research objective to planning and installing the system, and finally to analyzing the collected data.

In the first step, the objective of the monitoring measures is defined, specifying which aspects of the collected data should be analyzed and evaluated. This includes determining which parameters need to be monitored, what results are expected, and what resources are available for the monitoring process. This step involves developing the monitoring concept and preparing a tender. Additionally, success criteria for achieving the monitoring goals must be established, and suitable quality assurance methods (such as quality indicators, threshold values, and compensation methods) must be selected.

In the second step, the measurement system is installed on the structure. This step may also include retrofitting an existing measurement system. It is essential to conduct quality checks immediately after installation, such as function tests and plausibility checks, to ensure proper system performance.

In the third step, data collection is conducted to acquire the necessary information for subsequent analysis, which captures the impacts and/or responses of the structure. This step marks the beginning of the cyclical process of data collection, processing, and evaluation. At this stage, quantifiable quality measures are applied for the first time to ensure an objective assessment of data quality, independent of the specific task (these measures are detailed in Section 6). These quality indicators are also used in the next steps of data processing as they serve to monitor changes in data quality.

The fourth step, data selection, involves choosing the necessary and relevant data to answer the formulated question. This selection can be spatial (e.g., sensors in specific structural areas) or temporal (e.g., data from summer months). When applying machine learning methods, this step also includes

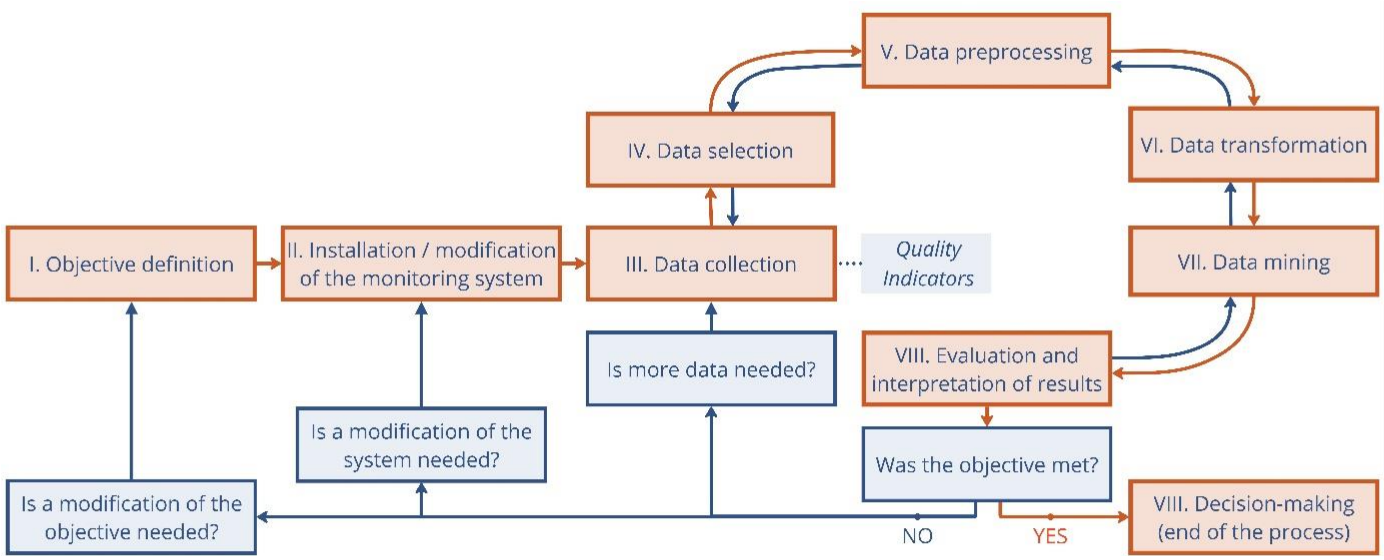

Figure 3. Data Processing Model in ANYTWIN project: Orange arrows represent the data processing workflow, while blue arrows illustrate the feedback loop, © Maria Walker, TUD.

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selecting the data that will be used in the feature engineering process.

Data preprocessing follows (step five), which includes data preparation tasks such as converting electrical signals into physical measurements, temperature compensation, time synchronization, signal cleaning, and data normalization. After each preprocessing step, a new data quality assessment is performed. The goal of data preprocessing is to enhance the inherent (task-related) data quality [19].

In the sixth step, system-dependent data quality is addressed. Data from various sources and measurement systems are standardized into a common structure and enriched with metadata. This standardization ensures that the data can be automatically processed by data mining algorithms in the subsequent step.

The seventh step involves the actual data analysis or data mining, during which information is extracted from the data. This process may involve simple calculations, such as determination of mean values, maximum and minimum values, or counting algorithms, as well as the training and application of complex machine learning models to identify patterns in the dataset and to detect characteristic sequences in the data.

The final step involves the evaluation and interpretation of the data mining results in relation to the initial question and predefined success criteria. The findings are assessed based on their validity, novelty, usefulness, and understandability. Based on these insights, necessary actions are determined, such as rehabilitation, load reduction, maintenance, reconstruction, or further monitoring measures. Additionally, this step includes a final assessment of the entire monitoring process and of the installed monitoring system to ensure its overall effectiveness.

6 QUALITY ASSESSMENT OF DATA USING QUALITY INDICATORS

To ensure reliable analysis and evaluation of structural behavior, the quality of measurement data must be guaranteed. It is crucial to eliminate anomalies in measurement data and deviations in time signals to achieve precise data evaluation of the structure's performance. However, measurement anomalies and deviations are inevitable and can be caused by various factors, including:

- Electromagnetic interference, leading to signal noise or data distortion
- Direct interventions on-site, such as maintenance work or sensor replacements
- Transmission errors, resulting in incomplete or faulty data
- Malfunctions in the measurement system, caused by calibration errors or hardware defects

In monitoring systems, which encompass interconnected and complex structures of measurement technology, data transmission, and IT aspects, anomalies in measurement data can occur. Therefore, it is essential to implement appropriate quality assessment methods to detect measurement anomalies early, correct or remove them if necessary, and optimize the monitoring system to ensure the reliability of the measured values.

As part of the ANYTWIN project, the requirements from measurement-based verifications are considered to systematically assess data quality. For this purpose, quality indicators have been developed to enable a structured and objective evaluation of monitoring data in terms of its quality. The development of these indicators takes various use cases into account, including:

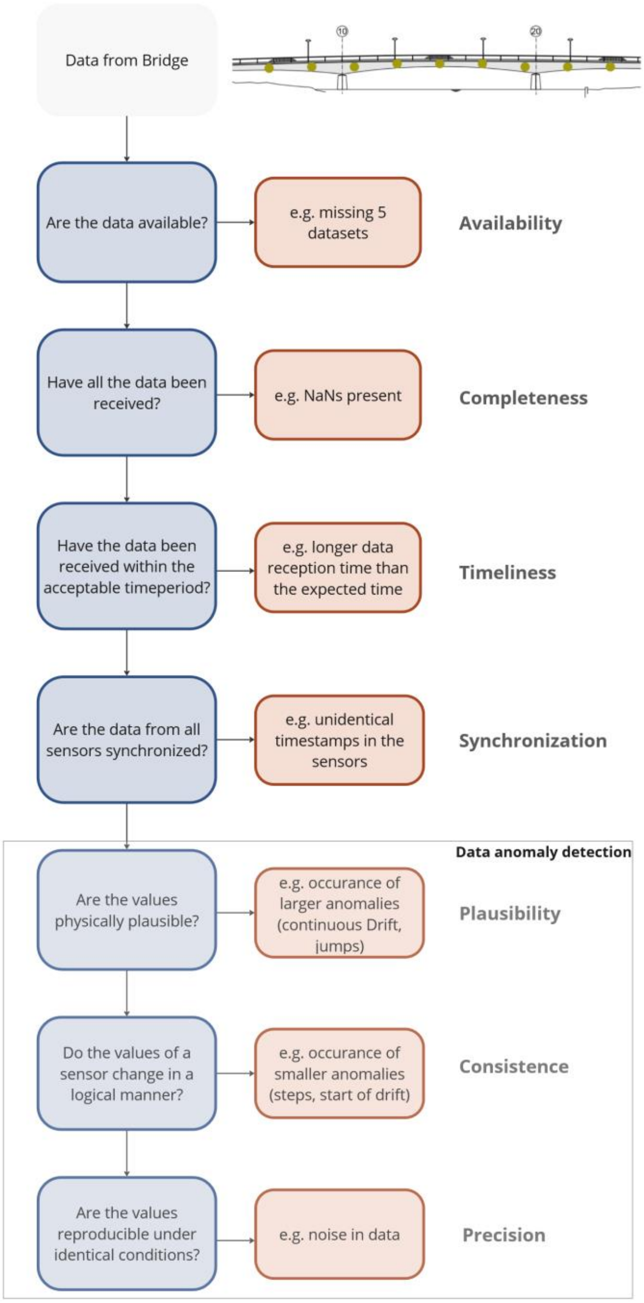

Figure 4. Overview of quality indicators and the addressed questions

- Measurement-based verifications, allowing for a precise assessment of structural safety,
- Continuous monitoring with an integrated alarm system for early detection of deviations,
- Digital twins, enabling detailed modeling and data-driven evaluation of structural behavior.

For this purpose, both the status of the measurement system and the quality of individual time signals at the sensor level are analyzed. At *the dataset level*, key questions include:

- Are the data available, complete, and up to date?

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- Are the measurements time-synchronized, ensuring that dependencies between two measured variables are reliably considered?

From these questions, the quality indicators availability, completeness, timeliness, and synchronization can be identified (see Figure 4).

Availability: Checks whether the expected measurement data has been received within a certain time window.

Completeness: Checks whether the received data contains all the required fields and sensor data records.

Timeliness: Checks if the measurement data arrives within an acceptable delay period.

Synchronization: Checks whether the multi-channel sensor data s synchronized in time.

The indicators that assess the condition of the measurement system – availability, completeness, and timeliness – can be quantified by calculating the percentage of available and non-missing data points within a defined time-period. To evaluate synchronization, the timestamps of individually generated time series (each measurement system) are analyzed.

The second aspect, *the sensor level*, focuses on detecting potential measurement anomalies, such as outliers, jumps, unusual temporal trends, drift, or signal noise. Based on these possible signal anomalies, the following quality indicators can be identified:

Plausibility: Checks whether the received values fall within physically plausible limits, allowing the identification of measurement anomalies such as outliers or jumps that are visibly apparent.

To assess the plausibility of the data and determine whether it falls within a physically realistic range, initial filtering or thresholding can be used to define permissible limit values. Plausibility calculation involves verifying whether the measurement value lie within these physically plausible limit. In a second step, advanced regression methods can be applied to detect further apparent measurement anomalies in the signal.

Consistency: Evaluates whether the change in sensor values is consistent with respect to environmental changes. This enables the detection of drift and noticeable patterns in temporal trends, such as step-like changes. While plausibility checks whether the data falls into a certain range, consistency compares current data with historical values and determines if the change in value is consistent with environmental changes (see Figure 5).

Consistency calculation is based on analyzing the differences between consecutive measurements. The standard deviation of these differences is determined and normalized by their mean value. A low standard deviation indicates high consistency, while a high standard deviation suggests irregular changes and, consequently, potential inconsistency. With consistency calculation, smaller or less apparent anomalies such as start of drift, step-formation can be detected.

Precision: Refers to the repeatability of measurements under identical conditions, ensuring the stability and reliability of sensor data. This helps to identify noise in the signal.

The precision of a measurement signal indicates the extent of value dispersion in repeated measurements. High precision means that the measured values are closely clustered, while low precision suggests random fluctuations and an increased level of noise. Mathematically, the precision assessment is based on the standard deviation of the measured values within a defined time window, relative to an acceptable variation range.

To quantitatively represent the indicators, the percentage of measured values that fall outside a defined tolerance range can be determined. Table 4 provides a comprehensive overview of the mathematical formulas used for detecting measurement anomalies, quantifying the indicators, and describing the relevant parameters.

The results of the quality indicators are also time series, but with a lower frequency than the actual measurement data, as they are based on aggregated time windows. Storing these indicators as time series allows for better integration into digital twins and facilitates the analysis of relationships between indicators, leading to a better understanding of the measurement data and its quality.

These indicators can be integrated into the partial safety factors of structural assessments as part of measurement-based verifications. This allows systematic consideration of

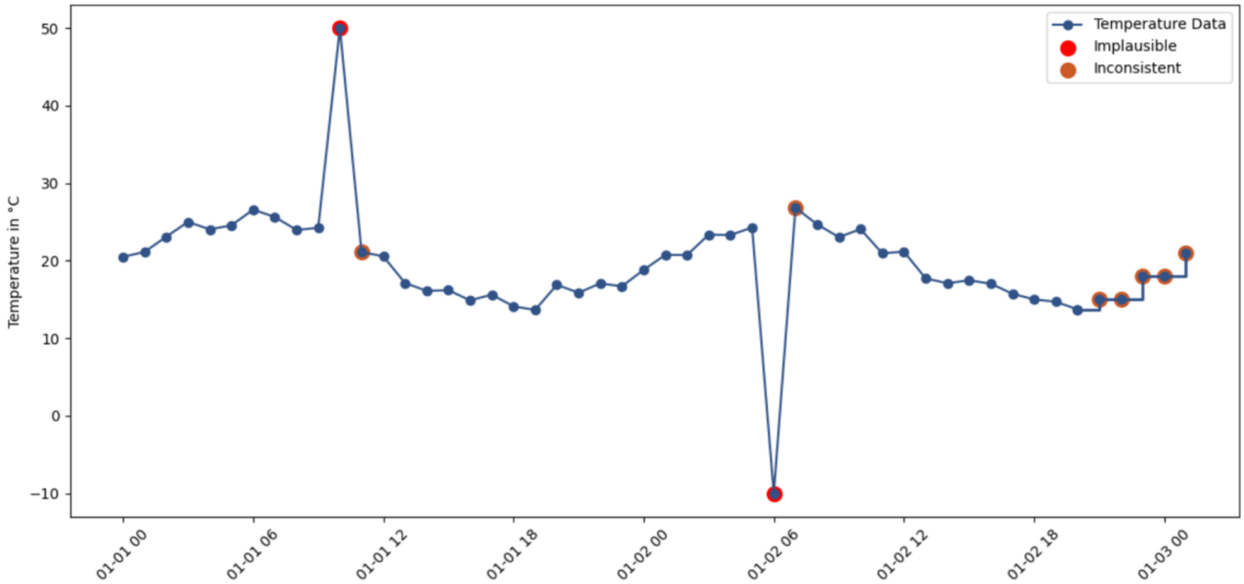

Figure 5. Example of temperature data containing implausible and inconsistent values

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uncertainties related to measurement technology, data transmission, IT, and numerical aspects and quantification in the form of modified partial safety factors. However, further research and development is needed to optimize these approaches and ensure their practical applicability.

Table 4. Overview of mathematical formulas for quantifying quality indicators

Indicator	**Mathematical Formula** for measurement errors detection	**Quantification of the indicators**	**Description of the parameters**
Availability	---	$\frac{N_{rec}}{N_{exp}} \cdot 100\ \%$	N_{rec} – Number of received data points N_{exp} – Total number of expected data points
Completeness	---	$\frac{N_{comp}}{N_{exp}} \cdot 100\ \%$	N_{comp} – Number of complete data points (without missing fields) N_{exp} – Total number of expected data points
Timeliness	$\Delta T = T_{now} - T_{last}$	$\frac{N_t}{N_{exp}} \cdot 100\ \%$	N_t – Number of data points received within the acceptable delay interval, T_{max} with respect to current timestamp ($\Delta T \leq T_{max}$) N_{exp} – Total number of expected data points T_{now} – Current time T_{last} – Time of last received data
Synchronization	$\Delta T = T_{sync}$ $T_{sync} = \lvert T_{S1,i} - T_{S2,i} \rvert$	$\frac{N_{sync}}{N_{exp}} \cdot 100\ \%$	N_{sync} – Number of synchronized data points N_{exp} – Total number of expected data points S_1 & S_2 – Measurements from Sensor1 and Sensor2 $TS_{1,i}$ & $TS_{2,i}$ – Timestamp of Sensor1 and Sensor2 at row i. $T_{sync} = \lvert TS_{1,i} - TS_{2,i} \rvert$
Plausibility	Level 1: Filtering and thresholding Level 2: with/without ML-model	$\frac{N_{pl}}{N_{exp}} \cdot 100\ \%$	N_{pl} – Number of plausible data points N_{exp} – Total number of received data points
Consistency	$1 - \frac{\sigma_{\Delta x}}{\mu_{\Delta x} + \epsilon}$ (or) with/without ML-model	$\frac{N_{con}}{N_{exp}} \cdot 100\ \%$	$\sigma_{\Delta x}$– Standard deviation of consecutive differences ($\Delta x_i = x_i - x_{i-1}$) $\mu_{\Delta x}$ – Mean of consecutive differences ϵ – Small constant (to avoid division by 0, e.g. 10^{-6}) N_{con} – Number of consistent data points N_{exp} – Total number of expected data points
Precision	$1 - \frac{\sigma}{R}$	$\frac{N_{pr}}{N_{exp}} \cdot 100\ \%$	N_{pr} – Number of data points without noise N_{exp} – Total number of expected data points σ – Standard deviation of the measurements R – Acceptable variation range

7 SUMMARY

Bridge monitoring is a key component of structural assessment to ensure safety and longevity. Despite its growing importance, monitoring is not yet a standardized procedure and is mostly implemented on a case-by-case basis. A structured approach can follow the recommendations of the DBV guidelines.

The sensor market is expanding rapidly, with increasingly intelligent and complex technologies for measuring temperature, material fatigue, deformation, and traffic loads. Innovations such as System-on-a-Chip (SoC) and edge computing, including Weigh-in-Motion (WIM) systems, enable greater automation of data collection but require systematic storage and analysis.

A precise data classification and standardization are essential for efficiently processing monitoring data and making it usable for digital twins or measurement-based verifications. Classification is based on positional reference (point, line or field measurements), time-based structure (continuous or discontinuous data), and time reference (instantaneous values, averaging or advanced methods such as Rainflow counting or FFT analysis).

Beyond the actual measurement values, metadata and additional information play an essential role in correctly interpreting the collected data. Metadata consists of machine-readable values assigned to sensors and measurement systems, while metainformation includes structured documentation details. A clear assignment of responsibilities for collecting and managing this data is necessary to maintain a consistent data foundation.

The ANYTWIN data processing model integrates various sensor types, measurement durations, and data processing methods, including machine learning, into a structured eight-step process. It follows established data processing frameworks (CRISP-DM, SEMMA, Fayyad, DBV guidelines, Farrar) and ensures data quality through an iterative feedback loop.

The process begins with defining the monitoring objective, followed by system installation and data collection. Next, data

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selection, preprocessing, and standardization ensure structured and high-quality input for data mining and analysis. Finally, the results are evaluated and interpreted to support structural assessments and maintenance decisions. This structured workflow enables continuous monitoring and reliable decision-making in structural health management.

A key aspect of data analysis is the evaluation of data quality using quality indicators, which are categorized into system level (availability, completeness, timeliness, synchronization) and sensor level (plausibility, consistency, precision). At the system level, data is assessed for availability, completeness, timeliness, and synchronization. At the sensor level, the focus is on evaluating the quality of individual measurement series, particularly in identifying measurement deviations and anomalies. To detect and quantify measurement anomalies and uncertainties, statistical methods such as filter functions, regression analyses, and standard deviations are applied. These methods enable a precise assessment of measurement data, contributing to improved data evaluation.

By storing these indicators as time series, they can be integrated into digital twins. Furthermore, they could be incorporated into measurement-based verifications by serving as a foundation for modified partial safety factors, considering uncertainties in measurement technology and data processing. While these approaches are promising, further research is required to enable their practical implementation in structural monitoring.

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