Plausibility Check and Exploring of Measurement Data at Digital Bridge Schwindegg

M.Sc. Diego Mediel-Cuadra *
M.Eng. Johannes Wimmer **
Dr.-Ing. Stefan Küttenbaum ***
Prof. Dr.-Ing. Thomas Braml ****

* University of the Bundeswehr Munich, Institute for Structural Engineering, Germany, diego.mediel@unibw.de
** University of the Bundeswehr Munich, Institute for Structural Engineering, Germany, johannes.wimmer@unibw.de
*** University of the Bundeswehr Munich, Institute for Structural Engineering, Germany, stefan.kuettenbaum@unibw.de
**** University of the Bundeswehr Munich, Institute for Structural Engineering, Germany, thomas.braml@unibw.de

Abstract:
The monitoring of bridge structures is one possible response to ageing infrastructure, which is a major concern in Central Europe. For this reason, current research trends are pursuing the development of new sensor systems, data transmission methods, data storage systems and evaluation algorithms. These endeavours are often referred to as digital twin. First prototypes have already been realised, the sensors installed, and measurement data recorded. However, to be able to analyse the data, it needs to be checked for plausibility. The plausibility check is demonstrated using the example of the digital bridge in Schwindegg, in which approximately 140 sensors were installed. This reveals sensors that measure well. However, the sensors that produce no, incorrect, or implausible values are also exposed. Furthermore, the study shows which sensors are suitable for which measuring tasks on the specific bridge and which are not. It highlights that it is not the number of sensors that matters but placing the right sensors in the right places.

Keywords: Structural Health Monitoring, Sensor Data, Data Science, Digital Twin

1 Introduction

In recent years, more and more reports have been published in German-speaking and European countries about ageing and increasingly damaged bridge infrastructure [1],[2]. The reasons for this are often a lack of recurring maintenance and renovation backlogs [3], increased traffic loads [4], environmental impacts such as flooding [5]or outdated or damaged building materials and construction methods [6]. Engineers and building operators have recognized the problem and are researching methods to overcome this significant challenge. One such alternative under investigation is Structural Health Monitoring (SHM), a method which has been utilised for several decades. Sensors are used to measure strains, vibrations, temperatures and subsidence in a structure, for example. In the context of Industry 4.0 and thus also automation, the concept of a system that autonomously monitors the structure is gaining traction [7]. This is supported by the further development of technology; mobile communications coverage is improving, and data transfer rates are increasing. Concurrently, the processing speeds of computers and microprocessors are increasing, and the storage hardware is becoming more compact and capacious. This facilitates more straightforward data acquisition and enhanced networking of systems of this nature. The technical capabilities for generating a digital twin are extant. The process encompasses data acquisition, data transfer, data storage, and data analysis, as illustrated in Figure 1. While the initial two domains can be addressed within the industry, given the existing extensive market for sensors and data acquisition systems, along with transfer modules and protocols, the latter remain predominantly in the research stage [8].

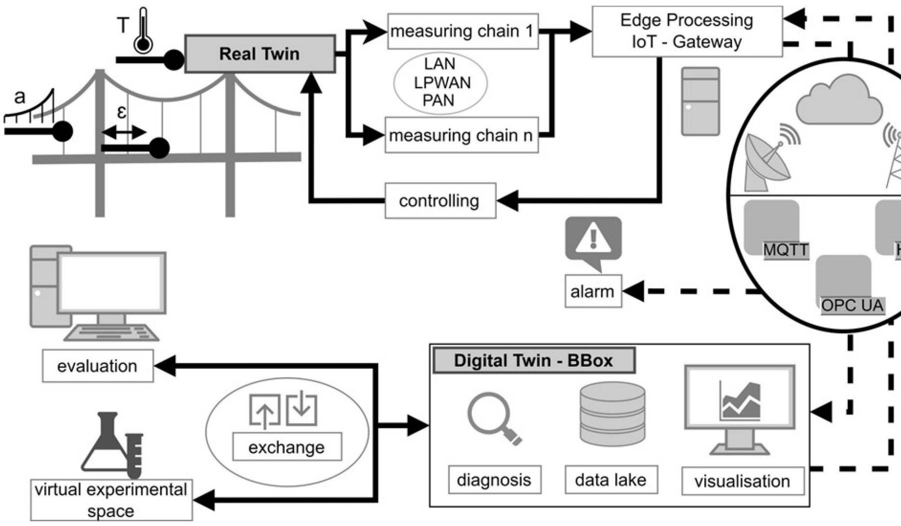


Figure 1: Data model of the realization of a digital twin [8].

For data storage, which is also the core of the digital twin, there are often only proprietary solutions that are not very scalable. The University of the Bundeswehr Munich is developing its own solution for this, which is based on Industry 4.0 asset administration shells [9]. The underlying ontology is also the one that is used for the documentation of most road bridges in Germany, so the skeleton of the digital twin can be generated quickly with the underlying import microservice. To make this skeleton intelligent, sensors are required that are intelligently evaluated. The basis for this is equipping bridge structures with sensors and checking whether these sensors are precise, reliable, suitable enough and measure with a sufficient sampling rate.

In this paper, the Isen bridge Schwindegg is presented as a field test for the data model shown in Figure 1. The following section presents a comprehensive overview of contemporary data processing methodologies and technologies. In order to ascertain the suitability of the different sensors for the respective measurement tasks, they are examined in a plausibility check. Consequently, deductions are made regarding the feasibility of implementing these sensors as alternatives in other projects.

2 Digital bridge Schwindegg (Germany) and its sensors

The bridge over the River Isen in Schwindegg, Germany, is a district road bridge with a length of approximately 19.8 meters. It was built in 2022 as part of a replacement construction project. The design of the bridge is comparable to that of many municipal bridges, with a single-span frame made of precast prestressed concrete girders with cast-in-place concrete supplement and an abutment foundation on bored piles [10],[11]. The bridge is located within the confines of a village, which is the reason for the speed limit being set at 50 km/h. The representativeness of the bridge, in conjunction with the feasibility of installing sensors during the construction process and the establishment of a fixed internet and power connection, make the bridge an ideal structure for a field test for a digital twin. Consequently, the bridge was equipped with approximately 140 sensors during construction, thereby providing approximately 170 independent measured values [10],[11]. The measurement concept is predicated on the static effects enumerated in [11], namely the rigidity of the frame corners, the moment distribution of the field and corners, the interaction between the bored piles and the abutment, the influence of temperature on a daily and seasonal basis, and the tracking of all vehicles that pass through the area.

The wired sensors are connected to the measuring devices, which are installed in the specially built technical block. As illustrated in Figure 2, the structure is accompanied by a depiction of several sensors. Table 1 provides a comprehensive list of the sensors in use and their respective specifications. The sensors were all georeferenced [8] and calibrated with load tests [12]. The structure has been the subject of almost continuous measurement since December 2022.

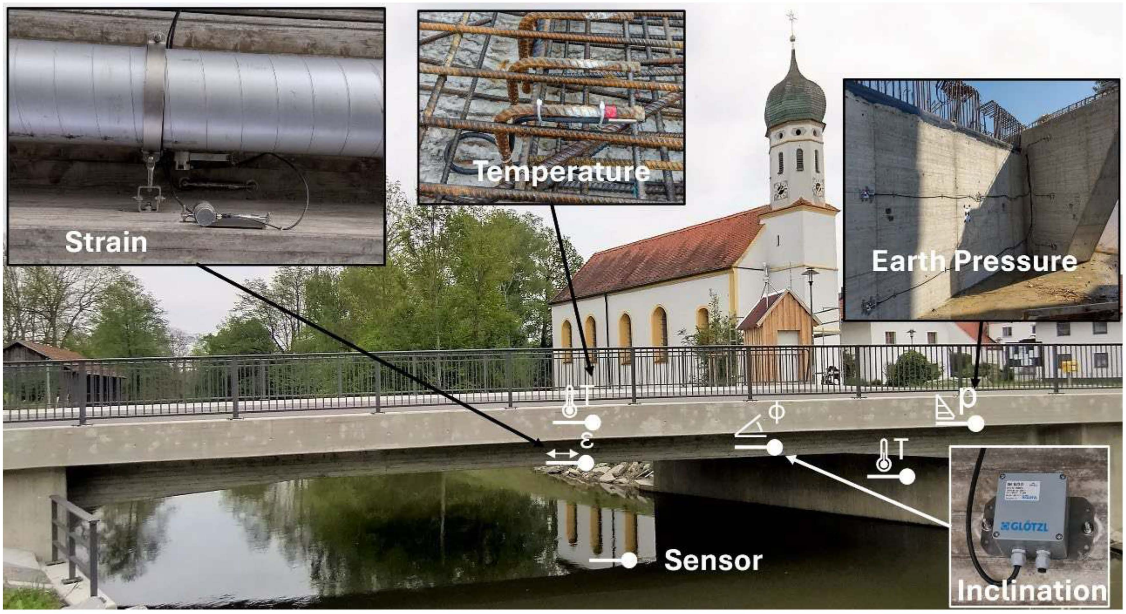


Figure 2: Selection of sensors at the Isen bridge Schwindegg.

Table 1: Comparison of measured variables and their system as well as principle, installation locations and sampling rates (from [10]).

Measureand	Quantity[1]		Sensor	Measurement position	Measurement rate [Hz]
	Physical	Data points			
Strain	60	60	Strain gauge, Fissurometer	Bored pile head, frame corner, precast beams (mid-span and bearing area)	10
Strain	22	22	Vibrating wire gauge	Bored pile head, frame corner, precast beams (mid-span)	0,1
Strain	2	2	Rotary encoder	precast beams (mid-span)	Up to 30.000
Strain	12	12 – >100.000	DFOS	Bored pile, frame corner, precast beams (mid-span and bearing area)	25
Temperature	37	34	PT100	Bored pile head, frame corner, precast beams (mid-span), abutment wall, bridge slab	0,003
Acceleration	6	18	MEMS	Precast beam (1/2, 1/3, 1/4)	200
Inclination	2	4	MEMS	Precast beam (1/4)	200
Inclination	3	6	MEMS	Abutment wall	10
Earth pressure	9	9	Piezo	Abutment wall	10
Deformation	4	5	Water level gauge	Bearing support points of precast beams	0,003
Weather data	12	20	Weather station	Technical block	0,003

[1] A physical sensor, which is installed in the bridge, can have multiple measuring directions, resulting in equivalent data points.

3 Data exploration – state of the art

The preliminary analysis of the sensor data recorded on the Isen bridge Schwindegg followed a structured data exploration workflow tailored to large-scale, high-frequency time-series data. Given the scale, thousands of CSV files each containing detailed sensor measurements, both manual and programmatic techniques were employed to evaluate the reliability, structure, and trends within the dataset, aligning with established data quality assessment frameworks in sensor networks [13],[14].

The first phase consisted of manually inspecting a representative subset of files. This enabled an intuitive understanding of the data's structure, including the number of rows and columns, sensor naming conventions, time formats, and metadata consistency. Manual inspection is a recommended best practice in time-series exploration, particularly in heterogeneous sensor datasets where automatic parsing may overlook subtle inconsistencies [15]. Building on the insights gained from manual review, automated analysis was conducted using Python, specifically leveraging the Pandas and NumPy libraries [16],[17]. Custom scripts were developed to systematically identify common data quality issues such as missing sensor values, duplicated records, inconsistent sensor naming, temporal gaps in the recordings.

These diagnostics are critical to assessing data plausibility and form the backbone of data quality assurance in large-scale sensor environments [13]. To manage noise and enhance interpretability, selected sensor measurements were aggregated over minute and hourly intervals using Pandas' resampling functions. This smoothing technique is widely adopted in time-series preprocessing to expose meaningful patterns while suppressing transient fluctuations [18]. Temporal aggregation also facilitates comparative analysis across sensors with variable sampling rates.

To further investigate data patterns, visualizations were created using Matplotlib, Seaborn, and Plotly. These libraries enabled both static and interactive graphical representations of time-dependent trends, which proved instrumental in identifying anomalies, outliers, and behavioral patterns across sensors. Visual exploration is a foundational method in exploratory data analysis, particularly when dealing with high-volume time-indexed datasets [19],[20]. While dedicated time-series databases like InfluxDB or OpenTSDB are commonly used for real-time sensor data streaming and querying, this study deliberately employed Jupyter notebooks in Python to retain flexibility and control during exploratory phases. Despite the data volume, the chosen approach supported sufficient scalability and transparency, which is especially advantageous in the research context.

4 Plausibility check of bridges sensors

To evaluate the reliability and suitability of the sensors installed on the Isen bridge Schwindegg, a three-step plausibility check was conducted. This procedure aims to determine whether each sensor behaves as expected in response to real-world structural or environmental stimuli. The plausibility check does not attempt to calibrate or correct sensor data but rather to assess whether the signal characteristics provide meaningful information under known physical events. The dataset comprises a diverse array of sensors deployed on the bridge, which is also summarized in Table 1 (Quantity – data points). For this study, the weather station sensors are excluded from the plausibility check, as their outputs were manually verified and confirmed to be functioning correctly. Also, the distributed fiber optic sensors (DFOS) and the acceleration sensors are not scope of this paper as they are not part of this kind of data set.

The first stage of the plausibility check evaluates whether a sensor can detect the passage of heavy trucks over the bridge. This test is based on data collected during a calibration campaign on 15 April 2025, between 06:45 and 07:45 UTC+0, when nine heavy truck crossings were conducted in succession.

Sensors were classified into three categories based on their response:

1. Clear response: Sensors that distinctly show nine measurable signal peaks corresponding to the truck crossings.
2. Noisy response: Sensors where the truck crossings are detectable but embedded within significant noise, requiring signal processing to clarify peak identification.
3. No response: Sensors that exhibit no identifiable signal variation aligned with the truck crossings.

Temperature and water level sensors were excluded from this step, as they are not expected to exhibit responses to dynamic loading events such as vehicle crossings due to their low measurement rate.

The second stage assesses the sensitivity of each sensor to daily environmental variations, particularly temperature-driven structural responses. The evaluation focuses on a one-week period from 15 to 22 July 2024, selected due to its marked temperature fluctuations that amplify the structural response of the bridge. The methodology involves overlaying each sensor's daily signal pattern with the reference temperature signal from the weather station. A sensor passes this check if seven consistent daily cycles (e.g., peaks or troughs) are observed, aligning with the daily temperature maxima and minima.

Sensors are grouped as follows:

1. Clearly responsive: Sensors that show seven distinct, aligned "peaks" or "troughs."
2. Weakly responsive with noise: Sensors that seem follow the daily temperature pattern but with substantial noise.
3. Not responsive: Sensors that do not show recognizable daily cycles correlated with the reference temperature signal.

In the third and final step, the long-term trends of the sensors are examined to determine their responsiveness to seasonal environmental variations. Sensor readings from 15 March to 2 December 2024 were plotted to observe macro-scale patterns, with a data gap between 17 October and 8 November due to storage system errors. This interruption did not compromise the evaluation due to the sufficient duration of the overall data window.

For sensors with high sampling frequencies (≥10 Hz), hourly averaged values were used to reduce computational overhead while preserving trend visibility.

Sensors were evaluated on the basis of long-term signal evolution:

1. Responsive sensors are those that display a progressive seasonal trend, typically returning to a similar value at the end of the year as where they started.
2. Non-responsive sensors are those lacking any discernible seasonal pattern, suggesting possible sensor failure, miscalibration, or installation error.

Passing this step is considered an indicator of structural and environmental coherence over time.

The plausibility check follows a sequential, elimination-based approach. At each step, sensors are evaluated based on their responsiveness to specific expected effects. Only those not fully validated in a given step proceed to the next:

Step 1: Truck Crossing Detection. Sensors that clearly identify all nine heavy truck crossings during the calibration test are considered plausible and do not proceed further. Sensors that respond noisily or not at all move to Step 2.

Step 2: Daily Environmental Effects. Sensors that exhibit a clear daily cycle correlated with temperature peaks over the one-week window are considered plausible and do not proceed further. Those with noisy or absent daily responses continue to Step 3.

Step 3: Seasonal Environmental Trends. Sensors that show a long-term seasonal pattern over the nine-month window are validated. Sensors without such trends are deemed implausible, potentially indicating malfunction or not relevant for this plausibility check.

5 Results

The three-step plausibility check was applied to a total of 142 sensors (excluding the weather station units), see Figure 3 where the results are summarized. Step 1, which evaluated the ability to detect heavy truck crossings, 21 sensors were identified as functioning correctly, responding to all nine events. An additional 14 sensors exhibited potential but noisy responses, suggesting that they might be usable with further signal processing. The remaining 107 sensors showed no discernible reaction to truck crossings and were thus forwarded to the second evaluation phase with the noisy sensors. In Step 2, the assessment of sensitivity to daily temperature-induced structural effects led to 89 sensors being classified as clearly responsive to daily cycles. 9 sensors showed noisy correspondence with daily temperature trends, while 23 sensors were unable to demonstrate any meaningful correlation and both were passed on to the third and final stage. Step 3 focused on identifying seasonal trends. Of the 32 sensors tested in this step, 20 exhibited seasonal patterns, returning to baseline levels by the end of the observation period. The remaining 12 sensors failed to respond to traffic loads and daily and seasonal temperature effects. In the next Chapter we discuss why these sensors have failed the plausibility check proposed.

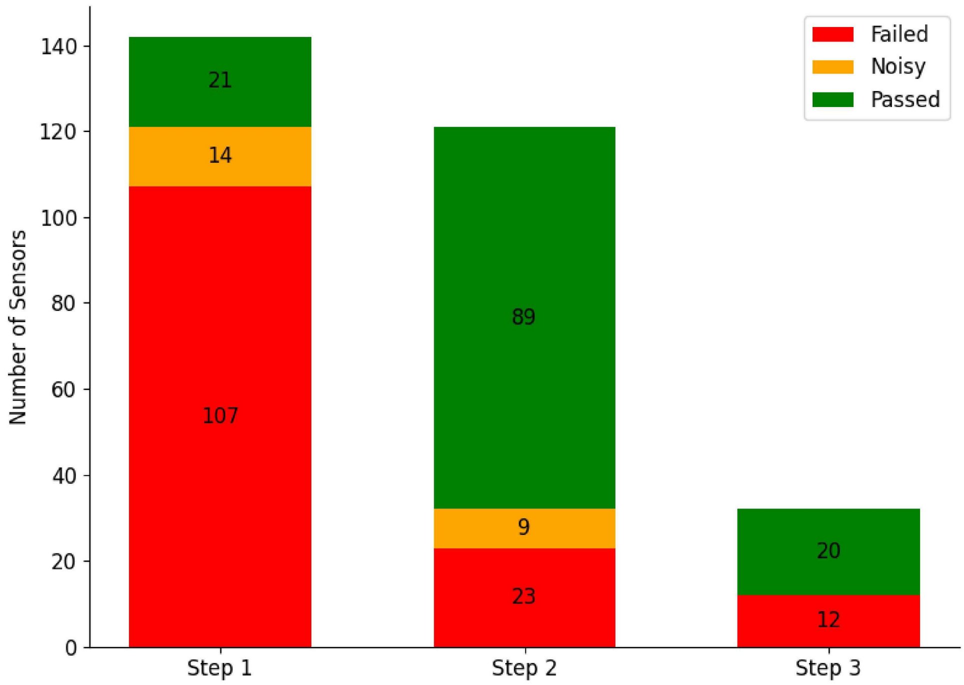


Figure 3: Plausibility check results from the three different steps. Inside each bar the number of sensors per category can be read. And the categories care differentiated by colors, green for "Passed", yellow for "Noisy" and red for "Failed". There are 142, 121 and 32 sensors in step one, two and three respectively.

Figure 4 upper plot illustrates the response of sensor DMS-FTB-3D, a strain gauge, clearly identifying each truck crossing event. The sensor records a contraction in response to the passage of trucks, characterized by distinct inverse peaks corresponding to each vehicle crossing. Sensor DMS-FTB-4U exhibits a response categorized as noisy. While certain truck crossing peaks are discernible, many peaks are obscured due to significant signal noise. Sensor DMS-FTB-3U does not display recognizable peaks corresponding to the truck crossings. In Figure 5, sensor DMS-FTB-3U, evaluated during the second stage of the plausibility check, demonstrates seven clearly identifiable signal peaks and troughs aligned precisely with daily air temperature variations recorded during the evaluation period. Thus, this sensor was categorized as responsive to daily temperature changes. Sensor DMS-FTS-3D shows a partially correlated yet noisy response pattern, indicating substantial interference that prevents clear classification as responsive to daily temperature variations. Sensor SCH-P10-1A-T, a temperature sensor positioned within the bridge structure, does not exhibit alignment with daily temperature fluctuations, likely attributable to its embedded location. However, Figure 6 (upper plot) demonstrates that SCH-P10-1A-T captures clear seasonal variations, reflecting higher structural temperatures in summer months and lower temperatures in winter months. However, sensor ERD-P10-3D, an earth pressure sensor, does not exhibit discernible seasonal variation, despite stable sensor measurements. The potential reasons for this behavior are discussed further in the subsequent chapter.

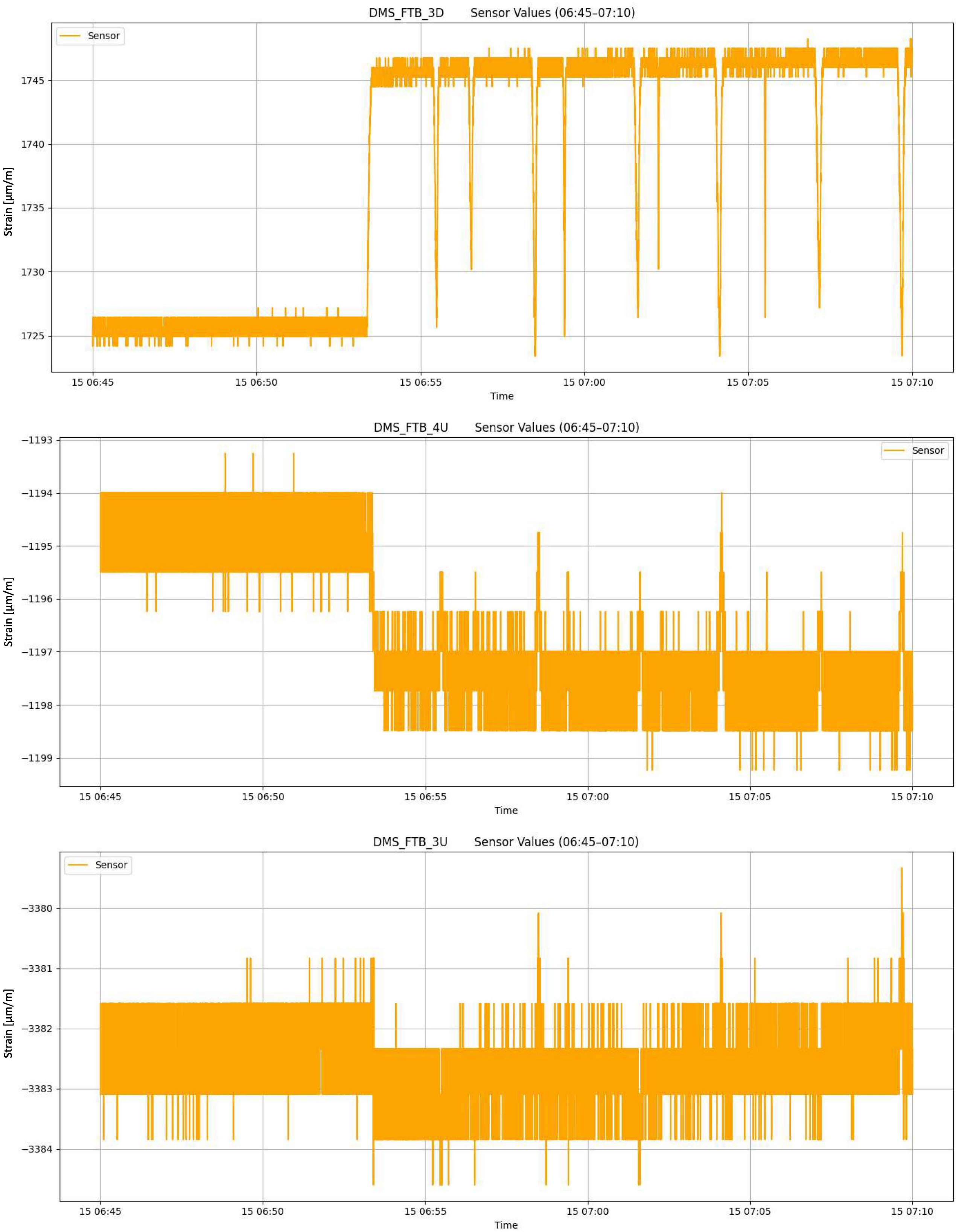


Figure 4: Three sample sensors from Step 1 (Truck Crossing Detection). All three sensors measure in µm/m. The upper, middle and bottom sensors are classified as Passed, Noisy and Failed respectively.

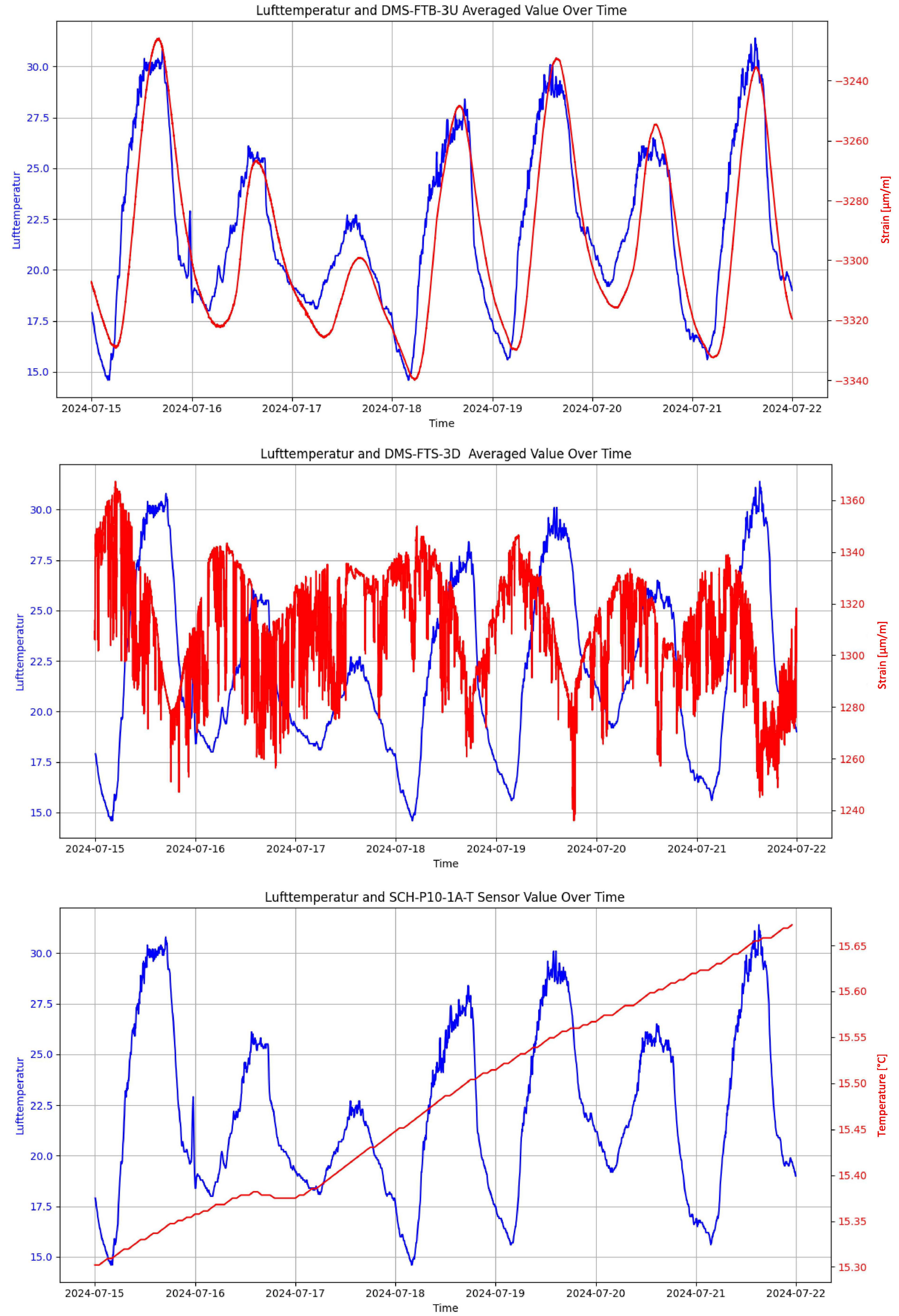
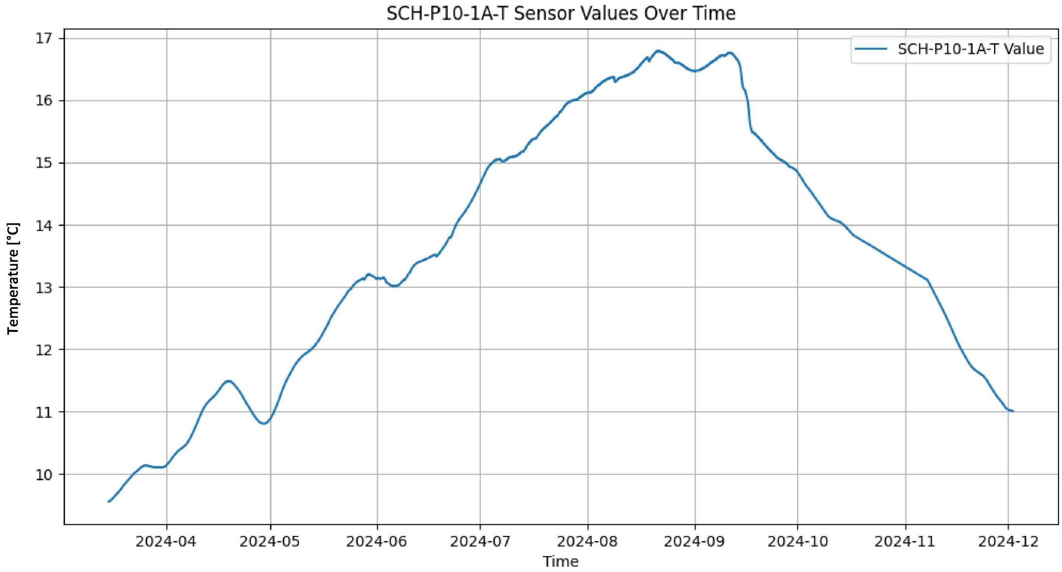


Figure 5: Three sample sensors from Step 2 (Daily Environmental Effects). "Lufttemperatur" stands for air temperature. The sensors DMS-FT-3U and DMS-FTS-3D measure in µm/m and the sensor SCH-P10-1A-T measures temperature in °C. The upper, middle and bottom sensors are classified as Passed, Noisy and Failed respectively.



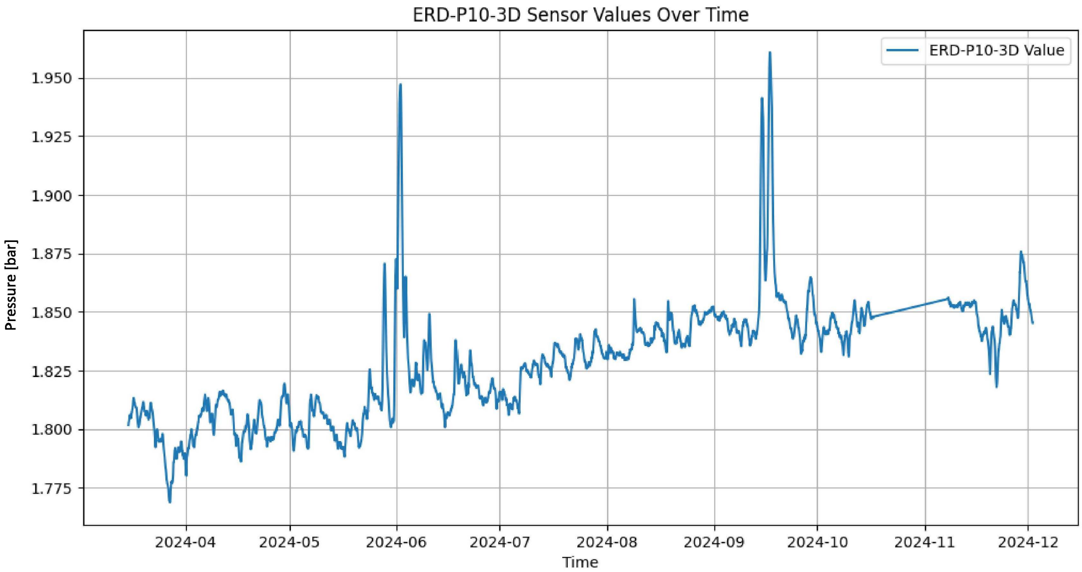


Figure 6: Two sample sensors from Step 3 (Seasonal Environmental Trends). The sensor SCH-P10-1A-T measures temperature in °C and ERD-P10-3D measures earth pressure in bar. The upper and bottom sensors are classified as Passed and Failed respectively.

6 Discussion

The primary objective of this study was to conduct a comprehensive plausibility check of sensors installed on the Isen bridge Schwindegg to determine their suitability for structural monitoring tasks. The sequential three-step plausibility methodology proved highly effective in distinguishing sensor responses to heavy truck crossings, daily temperature-induced structural variations, and long-term seasonal environmental changes. The results indicate that approximately 15% of the sensors (21 out of 142) accurately captured truck-induced structural events, confirming their immediate relevance for dynamic load monitoring tasks. A significant proportion, about 63%, demonstrated sensitivity to daily temperature variations, underscoring the prominence of environmental factors in sensor response behavior. Seasonal trends provided additional validation, affirming the utility of long-term monitoring to detect subtle yet critical structural changes over extended periods. However, the findings also exposed clear gaps, as 12 sensors failed all stages of plausibility checks, highlighting potential placement or technical issues. These outcomes reinforce the study's core conclusion that effective sensor placement and careful sensor type selection matter more significantly than mere sensor quantity.

The plausibility criteria centered primarily on traffic-induced dynamic responses and temperature-related structural changes. While these are critical indicators, other factors such as water pressure due to a rising ground water level resulting of flooding events, or non-temperature-driven environmental effects (e.g., humidity or wind) may significantly influence certain sensors' outputs, as seen in the earth pressure sensors. The failure of three earth pressure sensors towards the criteria of testing was likely due to their installation positions, far beneath the surface. Rather than indicating defects, these sensors appear responsive to hydrological conditions such as flooding (see Figure 6 bottom, the peaks are floods of approx. 1.5 m above mean level), which were not accounted for in the plausibility methodology. Similarly, two inclination sensors were positioned such that the dilation, contraction, and rotation effects due to temperature variations were not captured in their measurement directions. The current plausibility methodology, which excludes such site-specific conditions, might be insufficient to fully validate sensor functionality in certain contexts.

At least five strain gauges displayed clear signs of malfunction or defect, which was evident from the raw data. Furthermore, two fissurometers failed the plausibility checks without clear reasons, requiring further targeted investigations. The measurement frequency of sensors profoundly impacts their ability to detect dynamic traffic events. Sensors with low sampling rates might fail first step of the plausibility check not due to malfunction but because they were simply unable to capture rapid structural responses. Some sensors installed deeply within the bridge structure did not respond significantly to surface-level dynamic or temperature variations. Thus, sensor placement depth must be considered when evaluating sensor plausibility and functionality. It needs to be considered that the acceleration sensors installed in the Isen bridge were excluded from the plausibility check, leaving a gap in understanding their potential role and effectiveness in dynamic monitoring. Incorporating these sensors in future evaluations could provide valuable insights.

7 Conclusion

The outcomes of this study highlight significant opportunities for advancing structural health monitoring practices through strategic placement, and comprehensive data evaluation methodologies. Although certain gaps and limitations were identified, these challenges provide pathways for future innovation and improvement. The effectiveness of the plausibility check methodology represents a step toward more robust and reliable digital bridge monitoring systems. By addressing identified issues, refining sensor placement strategies, and expanding the evaluation criteria to include additional environmental factors, future research can further enhance the potential and reliability of digital twin technologies in civil engineering, ultimately contributing to safer, smarter, and more resilient infrastructure.

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