Contributions to Methodologies to Improve Sensor Data Quality of Cyber Physical Production Systems Through Digitalisation: A Use Case Approach

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***Abstract*—Cyber Physical Production Systems (CPPS) depend significantly on high-quality sensor data to function optimally, make decisions in real-time, and perform predictive maintenance inter alia. Nevertheless, the quality of sensor data in industrial settings is often affected by various factors such as environmental interference, hardware wear and tear, calibration drift, and intricate system interactions. This study introduces innovative methods to improve sensor data quality in CPPS through systematic digitalization strategies. By employing a use case methodology, we explore real-world production scenarios to pinpoint common data quality challenges and devise specific solutions. Our strategy integrates signal processing techniques, algorithms for detecting anomalies to establish robust frameworks for data validation and correction. The proposed methods offer practical, scalable solutions that can be adapted to various production environments, thereby enhancing the reliability and efficiency of cyber physical manufacturing systems. To illustrate the feasibility of our approach, we utilise the case study of a test bed.**

***Keywords*-Failure analysis; Sensor data quality; Sensor data error detection.**

I. Introduction

This section analyses the motivation, challenges, aims, research questions and contributions of this study. The objective of our study was to improve the quality of Cyber Physical Production Systems (CCPS) data through digitalisation by implementing a methodology to improve the quality of sensor data [1]. CPPSs consist of self-governing and collaborative components and subsystems. These elements are interconnected based on contextual factors, spanning all production levels. The integration extends from individual processes and machinery to comprehensive production and logistics networks [2].

For the sake of simplicity, within this study, we use the term “real-time”, since it is used exhaustively in the scientific and technical literature, but it should be understood that we are always referring to “near real-time”. To avoid confusion, the term "near real-time" implies that the required latency is not guaranteed, as in real-time systems, but only envisaged. In simple terms, for real-time systems, the latency of the system is part of its functional correctness; a near real-time system will function correctly if the required latency is inadvertently not achieved.

A. Motivation

In the realm of modern CPPS, there is an increasing dependence on extensive sensor networks to continuously track essential process parameters, equipment condition, and product quality. Despite this, ensuring high-quality sensor data remains a significant challenge that affects manufacturing efficiency, product uniformity, and operational safety. Inadequate sensor data quality can result in false alarms, undetected faults, inefficient process control, and ultimately higher production costs and diminished competitiveness.

Traditional methods for sensor validation often involve manual checks, statistical limits, or basic redundancy checks, which fall short in addressing the complexity and scale of contemporary production settings. These conventional techniques often miss subtle sensor degradation, issues with cross-sensor correlations, or context-specific anomalies that arise in dynamic manufacturing processes. Moreover, current solutions typically focus on sensor quality in isolation, neglecting the broader digital infrastructure and data processing workflows that define Industry 4.0 environments [3].

The incorporation of advanced digital technologies—such as machine learning, edge computing, and intelligent data processing—offers unprecedented opportunities to improve sensor data quality assessment and management. By developing systematic approaches that utilize digitalization capabilities, manufacturers can establish more robust, scalable, and adaptive sensor quality assurance systems. This research highlights the urgent need for comprehensive, digitalization-enabled strategies that can automatically identify, categorize, and address sensor data quality issues while seamlessly integrating with existing CPPS frameworks [4]–[6].

The practical validation of these methodologies through real-world applications demonstrates their relevance and effectiveness, providing manufacturers with actionable frameworks to enhance sensor reliability and, consequently, the overall performance of production systems.

B. Challenges

The adoption of digitalization-driven methods for enhancing sensor data quality in CPPS settings introduces numerous technical and practical hurdles that need to be overcome for effective implementation. Contemporary production sites utilize a wide array of sensor technologies from various manufacturers, each featuring unique communication protocols, sampling rates, data formats, and quality attributes. Crafting unified quality assessment strategies that can effectively manage this diversity while ensuring precision across different sensor types is a challenging task.

CPPS applications require immediate evaluation of sensor data quality to avert defective production or equipment damage. However, advanced quality assessment algorithms often demand substantial computational resources, leading to a conflict between processing complexity and the need for real-time performance, especially in resource-limited edge computing settings [7].

As sensor networks expand in size and complexity, maintaining consistent quality assessment performance while managing computational demands, communication bandwidth, and system maintenance requirements becomes increasingly challenging, particularly for large-scale industrial applications.

C. Aim

The main goal of this study is to create and validate comprehensive methods that utilize digitalization technologies to systematically enhance sensor data quality in CPPS. This research specifically aims to fulfill the following objectives:

Design and implement practical solutions capable of evaluating sensor quality in real-time while adhering to the strict performance standards of industrial production settings. This involves creating efficient algorithms suitable for edge computing platforms and resource-limited operational conditions.

Validate the practical applicability and effectiveness of the proposed methods through detailed case studies in actual production environments. The Suspension Motion Simulator case study serves as the main validation platform to assess algorithm performance, detection accuracy, and operational feasibility.

Offer clear guidelines and implementation strategies that allow manufacturers to incorporate these digitalization-enabled quality improvement methods into existing CPPS infrastructures with minimal disruption to ongoing operations.

D. Contribution

This study introduces several innovative advancements in managing sensor data quality within CPPS through digitalization: Development and validation of a practical strategy for real-time sensor quality assessment in production settings using optimized algorithms suitable for edge computing platforms.

Establishment of a systematic approach for validating sensor quality improvement methods through controlled industrial case studies. The Suspension Motion Simulator implementation showcases the practical applicability of the proposed methods and provides measurable performance metrics for evaluation.

Contribution of a modular, scalable approach adaptable across different production scales and sensor network complexities, from single-machine implementations to facility-wide deployments. These contributions collectively enhance the state-of-the-art in sensor data quality management for modern manufacturing systems and offer practical tools for improving production reliability through digitalization technologies.

E. Paper organisation

The structure of this paper is outlined as follows. An overview of relevant existing research pertaining to the described problem is provided in Section II. A detailed description of the strategy is presented in Section III, whereas Section IV demonstrates the feasibility of this strategy through an example. The presentation of the main results and discussions based on these results constitute the content of Section V. Finally, Section VI summarises this contribution and draws perspectives for future work.

II. Related work

Recent studies in sensor data quality management for CPPS have concentrated on tackling essential calibration issues and creating digitalization-driven solutions for industrial settings [8].

The phenomenon of sensor drift has been thoroughly investigated across various sensor technologies [9] illustrated that zero-point drift has a substantial impact on measurement precision in mechanical spectroscopy applications, while [10] pinpointed bulk equilibration effects as the main reason for baseline drift in metal oxide gas sensors. The detailed analysis by [11] showed that environmental factors, wear-and-tear, and manufacturing inconsistencies lead to gradual sensor deterioration, with drift rates differing significantly among sensor types and operating conditions. Electrochemical sensor systems display unique drift characteristics, as evidenced in [12], where both exponential sensitivity decline and linear baseline shifts occur concurrently. Temperature-induced drift mechanisms have been particularly well-documented, with [13] demonstrating that thermal expansion coefficients and bridge circuit asymmetries are key contributors to zero-point errors in pressure sensors.

The use of machine learning techniques for assessing sensor quality has garnered considerable interest. [11] effectively applied isolation forest algorithms for real-time drift detection, achieving early recognition of sensor degradation patterns. Multi-sensor array strategies using orthogonal signal correction have been developed by [14], showing effective drift compensation through baseline manipulation and partial least squares regression. Advanced compensation methods incorporating neural networks and polynomial fitting have been explored by [15], indicating that radial basis function networks can accurately model complex non-linear temperature relationships in sensor systems. These methods allow for automatic calibration adjustments without the need for frequent manual intervention.

Practical deployment considerations have been addressed through various industrial case studies. [16] developed federated learning approaches for electronic nose systems, facilitating cross-facility knowledge sharing while preserving data privacy. The research demonstrates that multivariate calibration models can be effectively updated using distributed sensor networks without compromising proprietary information. Temperature drift compensation strategies have been validated in industrial settings, with [17] providing quantitative methods for calculating zero and sensitivity drift coefficients. These strategies enable predictive maintenance scheduling and reduce the need for frequent calibration in production environments.

While existing research tackles individual aspects of sensor quality management, comprehensive frameworks that integrate real-time detection, automated compensation, and industrial-scale deployment are still limited, see [18] for an example of heterogeneous networks. Designing heterogeneous sensor networks presents the challenge of ensuring that sensors can collaborate effectively despite their differences. This involves creating protocols and algorithms capable of managing data flow, maintaining data quality, and optimizing energy use, etc. A generic model is developed [19], yet it is recognized that current industrial monitoring relies on basic Statistical Process Control limits. Most current approaches focus on single sensor types or specific drift mechanisms, lacking the comprehensive methodology needed for diverse CPPS environments. This research addresses these gaps by developing an integrated digitalization framework that combines multiple quality assessment techniques with practical validation through industrial use cases.

III. Strategy

In this section, we explicitly delineate the focus of the underlying investigation and outline a strategy that can be employed to achieve these goals. This is in relation to the detailed use case study presented in Section IV. We succintly present a list of possible sensor outlier and analyze as illustrative the calibration related outliers [19]–[35]. This list includes crucial types, but it is not comprehensive.

- **Sensor Outliers and Common Causes:**
  - **Calibration-Related Outliers:**
    - Gradual drift - Over time, sensors become less accurate due to factors like aging components, temperature fluctuations, or material wear.
    - Baseline shift - The initial reading changes, resulting in all measurements being consistently offset by a fixed amount.
    - Sensitivity errors - Changes in the sensor's sensitivity lead to readings that are consistently too high or too low by a certain percentage.
    - Non-linear response - The sensor's response becomes non-linear throughout its range, leading to inaccuracies at specific measurement points.
  - **Environmental Outliers:**
    - Impact of temperature - Extreme heat or cold leading to sensor readings deviating from standard ranges.
    - Humidity disruption - Moisture influencing electrical sensors or optical parts.
    - Electromagnetic interference (EMI) - Radio waves or electrical fields distorting sensor signals.
    - Vibration-induced noise - Mechanical vibrations causing inaccurate readings in accelerometers or pressure sensors.
  - **Physical Damage or Contamination:**
    - Fouling - Accumulation of dust, oil, or chemicals on sensor surfaces impacting optical or chemical sensors.
    - Corrosion - Metal components in pH sensors or electrochemical devices undergoing oxidation.
    - Physical obstruction - Items obstructing ultrasonic or optical sensors.
    - Wire degradation - Damaged or corroded connections leading to sporadic readings.
  - **Installation and Mechanical Issues:**
    - Installation issues - Loose sensors causing vibration disturbances or positional inaccuracies, loose connections, broken cables, etc.
    - Thermal expansion - Variations in temperature leading to mechanical stress and alterations in measurements.
    - Pressure seal failures - In pressure sensors, resulting in faulty atmospheric compensation.
  - **Electronic and Signal Processing Outliers:**
    - Errors in converting analog signals to digital - Issues like bit flips or quantization problems during digitization.
    - Fluctuations in power supply - Variations in voltage that impact sensor excitation and output.
    - Ground loops - Signal corruption due to electrical noise from improper grounding.
    - Crosstalk in multiplexers - In systems with multiple channels, signals interfering between channels.
- **Advanced Outlier Categories:**
  - **Communication and Data Transmission Issues:**
    - Packet loss - Missing data points in wireless sensor networks creating gaps or interpolation errors.
    - Timing synchronization errors - Clock drift causing timestamp misalignment in multi-sensor systems.
    - Protocol errors - Communication protocol failures leading to corrupted or duplicated readings.
    - Buffer overflow - Data acquisition systems dropping samples during high-rate collection.
    - Performance problems with data transfer - network too slow or computing power (CPU overloaded)
  - **Software and Firmware Outliers:**
    - Errors in floating-point precision - Accumulation of rounding mistakes during computations.
    - Firmware issues - Software malfunctions leading to consistent errors or sporadic incorrect readings.
    - Memory corruption - RAM faults impacting stored calibration data or processing algorithms.
    - Stack overflow - Program failures causing sensors to produce default or erroneous values.
  - **Operational Context Outliers:**

  * Saturation - Occurs when sensors hit their maximum measurement capacity, leading to clipping or wrapping around.
  * Hysteresis effects - Sensor outputs influenced by previous measurement history.
  * Settling time violations - Taking sensor readings before they have stabilized following changes in input.
  * Sample rate aliasing - Insufficient sampling of rapidly changing signals, resulting in misleading low-frequency content.

Failure Mode and Effects Analysis (FMEA) methodologies present several significant benefits for ensuring the quality of sensor data. By identifying potential sensor failure modes before they happen, FMEA allows for preventive actions instead of reactive ones. It ensures thorough coverage by investigating all possible sensor failure scenarios, such as drift, calibration errors, environmental interference, and physical damage. Additionally, it offers a data-driven framework to prioritize which sensor quality issues need immediate attention. In dynamic manufacturing settings, FMEA is most effective when integrated with real-time monitoring and Artificial Intelligence (AI)-based anomaly detection systems [36].

In the following, as an example, we give some Python and R utilities that can be used to address calibration related outliers [37]–[42]:

Python Tools:

- scipy.optimize.least_squares() - Utilized for robust calibration fitting that includes outlier management
- sklearn.linear_model.RANSACRegressor() - Employed for calibration regression that is resistant to outliers.
- scipy.stats.zscore() - Applied for detecting statistical outliers in calibration datasets.

R Tools:

- MASS::rlm() - Used for fitting robust linear models in calibration.
- robustbase::lmrob() - Implemented for robust regression with outlier identification.
- RobustCalibration package - Designed for robust Bayesian calibration techniques.
- car::outlierTest() - Utilized for statistical testing of outliers in calibration models.

IV. USE CASE

This section demonstrates the practical application of the solution concept described in Section III. The concept was implemented and validated using the "Suspension Motion Simulator" (SMS) case study at the Institute for Automotive Engineering, Technische Universität Dresden, Germany (Figure 1), see [43]. The progressive digitalization of CPPS establishes the foundation for AI-driven approaches, including data mining and predictive analytics. Within this context, the case study aimed to develop a functional strategy for identifying sensor data errors on the simulator in real-time. The following key areas were explored:

- Outlining the test bench setup, including integrated sensors and their roles in various testing tasks.
- Examining relevant measurement chains to identify potential error influences and their impact on signal curves.
- Investigating algorithms for identifying and mitigating common data quality issues caused by test bench malfunctions and environmental factors.
- Demonstrating error detection and categorization in data using MATLAB or a similar development tool.

The resulting algorithm enables immediate diagnosis of data quality issues during the measurement process. The aim is to create a computer model that is as accurate as possible, thereby enabling simulation.

Many measurement data sets contain errors and other anomalies. However, these must be error-free for machine learning applications, a context-sensitive analysis is desirable. Errors within data sets can lead to mistakes in analysis, resulting in misinterpretations within the given context and, eventually, incorrect decisions. This may cause defects in product quality or harm the CPPS. Ultimately, this poses a major challenge to the adoption of ML in production due to the lack of trust in AI. It is therefore necessary to detect and eliminate errors. If this is not possible, the data set must be excluded and regenerated. In most cases, however, this is not possible because the vehicles can only be on the test bench for a limited time. To solve this problem, it is necessary to detect errors as quickly as possible and repeat the measurements. In order to obtain a sufficiently large error-free data set, old measurement data must also be checked again for accuracy and merged with newly generated measurement data.

The script developed in the course of this work and the algorithm behind it should make a major contribution to this. By quickly detecting a selection of errors, it should be possible to repeat the measurements on the same day, thereby relieving the pressure on the production team and customers and saving time and money. In addition, it should enable the creation of an error-free database for further use with machine learning.

A. Test bench setup

The test bench, which was supplied by the manufacturer MTS Systems (MTS), 2021 , is supplemented by additional systems installed by the chair. The test bench is an integral component of the parameterisation line under development at the vehicle technology test centre, German: Fahrzeugtechnisches Versuchszentrum (FVZ). It will eventually facilitate the largely automated determination of a vehicle's parameters. The objective is to develop a highly precise computer model to enable simulation. The test bench can be divided into four basic subsystems, which consist of further complex systems and are explained below.

The initial subsystem is the test bench itself, which is supported by a substantial foundation designed to dampen vibrations using three air springs positioned at its corners. Steel rails cover the foundation's base, enabling the attachment of various systems. The most significant system affixed in this manner is the test bench. Positioned atop this are two

Figure 1. Main table of the test bench and its four electromagnets [43]. Four powerful electromagnets are placed on the main table, to which the car sill or a suitable adapter can be clamped.

tables, both of which can be vertically adjusted to fit vehicles of varying sizes. The main table is equipped with four strong electromagnets, allowing for the clamping of a car's sill or an appropriate adapter (refer to Figure 1).

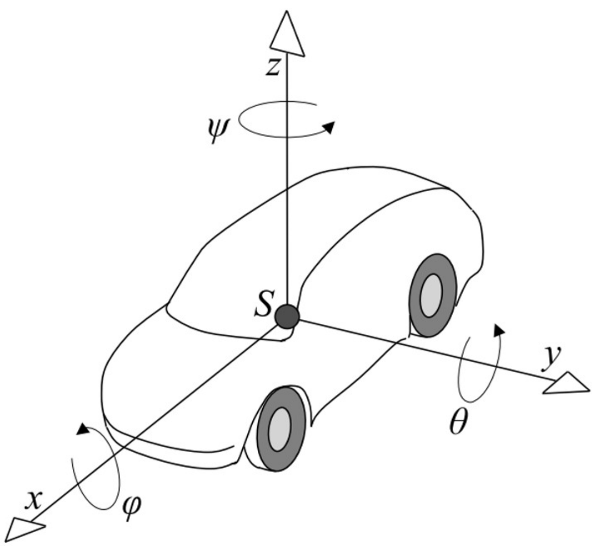

Figure 2. Vehicle coordinate system according to DIN 70000. In this figure, φ represents the roll angle, θ indicates the pitch angle, and the yaw angle ψ is also shown [43].

When the hydraulics are activated, the stamps can apply a force of up to 20,000 N and operate swiftly, necessitating careful handling. The platforms are designated as Right Front (RF) on the right side in the direction of travel and Left Front (LF) on the left side. Figure 2 illustrates a sketch of the test bench coordinate system. In this figure, φ represents the roll angle, θ indicates the pitch angle, and the yaw angle ψ is also shown. The tyre's coordinate system aligns with the vehicle's coordinate system and originates at the center of the rim.

The test bench is operated by a controller, which is linked to a computer located in a separate room for safety purposes. This computer hosts a virtual machine that runs the control software provided by MTS.

This management approach, as specified by the manufacturer, ensures the software operates reliably across various operating systems. Additionally, the program allows for the control of different platforms.

Once the set-up procedure is complete, the vehicle is hoisted onto the test bench using a crane. This involves sliding four claws beneath the car. On the test bench, the vehicle is secured.The set-up process includes installing measurement equipment like potentiometers, cable gauges, and other instruments. Additionally, the vehicle's weight and dimensions are recorded. This data is crucial for accurately setting up the vehicle on the test bench.

The Aramis SRX optical measurement system, see Figure 3 created by GOM, a company that specializes in optical measurement technology (GOM, 2021), is installed on the test bench. It is positioned on two platforms, one on each side of the bench, allowing for the detection of even the slightest movements of the chassis or rims.

Figure 3. IT concept of the "Aramis SRX optical measuring system" test stand [43].

For this purpose, reflection points are affixed to the relevant assembly and logged into the software. This setup permits the measurement of movements relative to the primary coordinate system, as illustrated in Figure 2, located at the vehicle's center. During recording, these points are illuminated with blue light to facilitate tracking. The reflection points bounce back this light, allowing each point to be distinctly recognized.

Various tests can be carried out on the test bench. In most cases, however, the so-called standard tests are carried out. These refer to nine basic test types, which are listed in the following Table I.

Table I offers a concise summary of the fundamental tests. Numerous variations and specific instances exist for each of these standard test scenarios. The table includes the tests that

TABLE I. OVERVIEW OF THE INDIVIDUAL STANDARD TESTS ON THE TEST BENCH

Test code	Description
T01	Vertical test
T02	Roll test
T03 a.)	Lateral compliance test aiding
T03 b.)	Lateral compliance tests opposing
T04	Longitudinal Braking Compliance Test
T05	Longitudinal Acceleration Compliance Test
T06 a.)	Align Torque Compliance Aiding
T06 b.)	Aligning Torque Compliance Opposing
T07	Steering Ratio Tests
T08	Cornering Test
T09	Longitudinal Compliance Test

are most frequently conducted. Additionally, there is a test definition from MTS that outlines various tests, their functions, and other pertinent parameters (MTS Systems, 2020). These serve as the standard for 'Kinematics and Compliance' test benches. The tests employed by the test bench team closely resemble or are derived from these.

There are numerous other testing scenarios that can be explored. For instance, white noise, which produces a random signal with a particular amplitude and frequency, can be utilized. Additionally, one can create a completely self-generated signal and store it for future playback. This capability allows for any dynamic excitation within the operational limits of the test bench. It also enables the simulation of actual road conditions to identify the source of a noise. However, generating such a signal demands significant effort.

During the initial phase of the evaluation, a mat file is generated from the measurement data. This task is accomplished using a Matlab script developed by the test bench team. The script consolidates the different files from both the test bench and the Aramis system into a unified file. Consequently, the mat file encompasses all the necessary data for evaluation. Following this, another script is employed to plot the data, resulting in various diagrams that depict the measurement data over time. These diagrams are instrumental in evaluating the quality of the measurement data.

During the second phase, the data undergoes verification. Initially, it is determined whether all measurement data channels are included or if the signal from either the right or left side of the test bench is absent in a diagram. If everything is in order, the next step involves evaluating the quality of the measurement data, focusing on the noise levels across different channels. Should one channel exhibit significantly more noise than the others, the measurement must be redone. Subsequently, the measurement plan is reviewed to confirm that all documented forces and positions have been achieved. If discrepancies are found, they may have arisen from errors in inputting boundary data or during the test bench's execution. Following this, the reproducibility of the graphs is assessed by examining the hysteresis, which should generally follow similar trajectories. The final step in data verification involves checking for errors, such as anomalies like jumps or missing values. If the graphs display no unacceptable jumps in measured values and the lines are mostly continuous, the measurement data is considered acceptable. Once all these checks are completed, a decision can be made on whether the measurement needs to be repeated or if it is suitable for further analysis.

When examining a system as intricate as a test bench, a methodical approach is crucial. To address all elements thoroughly and impartially, it is important to first identify the main issues, which will serve as a foundation for subsequent analysis. The next chapter outlines the techniques employed for this purpose.

To evaluate the test bench, a comprehensive examination of the entire setup was conducted. The primary inquiry was: 'What subsystems are identifiable within the complete test bench, and how can these be effectively reduced to the essential components?' To address this, a mind map was developed, and once all systems were documented, efforts were made to discern a pattern. This approach was intended to ensure that the test bench analysis was thorough and comprehensible. The subsystems identified are:

- Suspension motion simulator
- Hydraulic unit
- Test specimen
- Crane
- Aramis SRX

As the work progressed, the individual subsystems and their roles were analyzed. The suspension motion simulator was the most detailed among them. To clearly outline all its functions, an additional breakdown of the SMS was required. The emphasis was on its operation and design, potential configurations, and internal data logging. Furthermore, the possibility of integrating other measuring devices, such as potentiometers, with the test bench was also explored.

Initially, the chosen errors were organized in a logical sequence for verification. It is illogical to assess different noise levels when entire channels are absent or filled with empty values. Consequently, it was determined that the data's completeness should be verified first, followed by the functions that necessitate complete measurement data, such as noise analysis.

Subsequently, the measurement data underwent a thorough review. To identify the algorithm's error, it was necessary to find a logical or mathematical method for detection. This required a detailed analysis of the channel curves and the identification of an appropriate Matlab function.

Utilizing name lists guarantees easy scalability, allowing for the addition of new channels in the future as needed. The program will then verify these additions. To determine if the function accurately identifies errors, faulty data records are accessed, and an additional method known as error injection is employed. This involves manually introducing the desired anomalies into the measurement data. For instance, in jump detection, an extra jump was artificially created to observe how the program responds in such scenarios.

B. Important aspects for measurement data quality

To date, adherence to these criteria in the Suspension Motion Simulator has been maintained through manual oversight of the measurement data. The newly developed algorithm aims to autonomously verify the criteria of completeness and correctness, paving the way for future automated verification and assessment of measurement data, with the ultimate goal of integrating machine learning into the test bench.

C. Error detection and categorisation in measurement data

In a complex system like the Suspension Motion Simulator, various errors can arise. To create a Matlab script – the simulation requires a Matlab file, hence Matlab was chosen for identifying the errors – capable of identifying these errors and notifying the responsible engineer, a thorough understanding of each specific error is essential. This chapter outlines the errors that have been encountered, explores methods for detecting them, and examines the design and operation of the algorithm that has been developed.

Numerous errors can arise with the suspension motion simulator. Some of these errors occur simultaneously, while others happen independently. A concise summary of the errors encountered so far is presented in Table II. Errors that are the focus of this paper are explained in more detail below.

TABLE II. THIS TABLE CONTAINS ERRORS THAT HAVE OCCURRED DURING TEST BENCH OPERATION TO DATE.

Error	Source	Description	Freq.
Missing channels	GOM	Entire channels missing from measurement data	Rare
Missing points	GOM	Measurement points missing	Rare
Incorrect data	GOM	Malfunction in Aramis file	Rare
Jumps	GOM	Data jumps implausibly	Very rare
Overload	SMS	Force/torque exceeded, emergency stop	Frequent
Controller error	SMS	Controller error causes problems	Very rare
Irregular graph	Hydraulic	Oil viscosity changes due to heating failure	Very rare
Overheating	Hydraulic	Oil too warm, cooling unable to maintain temp	Very rare

If Aramis captures entirely inaccurate measurement data, the issue typically lies within the loaded file. Before initiating a measurement, it is essential to input and group the marked individual points into the system. Additionally, distances between various coordinate systems can be established. Contours, such as a steamer on the front axle, can also be scanned at different locations and subsequently saved as cylinders in the file. Occasionally, these objects might be rotated in space, deviating from their original positions, leading to erroneous measurement data. To safeguard the test bench from damage, it is equipped with an emergency shut-off mechanism that activates when specific distance or force thresholds are surpassed. If the forces become excessive, the tire might slip on the corundum of the measuring platforms, reaching an unacceptable force or distance value. Furthermore, if the steering wheel is obstructed by a steering wheel lock, the existing torque around the Z-axis (refer to Figure 2) can become so substantial that it causes slippage. This also results in unacceptable values, prompting the test bench to enter emergency shutdown mode. During an emergency shutdown, the measurement process is halted, and the hydraulics are deactivated.

A highly uncommon error is initiated by the controller, which then assumes control of the test bench. Should a malfunction occur, issues may arise, such as when employing the ’platforms away from wheels’ script. In such instances, the test bench becomes unresponsive and powers down. Additionally, if the hydraulic oil is not at the appropriate temperature, complications can ensue. Typically, a heater within the hydraulic unit regulates the temperature. However, if the necessary sensor malfunctions, emergency mode must be activated. In this mode, the oil is warmed solely by the test bench’s movement. A temperature that is too low can cause a wave-like pattern in a graph that would otherwise be sinusoidal. Conversely, if the hydraulic oil becomes excessively warm, issues will also occur. Should the hydraulic unit’s cooling system fail to provide adequate power, it will shut down, leading all test benches to enter emergency shutdown. This situation has been a rare occurrence in the past.

On the test bench, there are several distinct measuring chains, each comprising various stations where measurement data is generated, processed, or transmitted. This reseach focuses solely on the optical measuring system chain, as the specific errors identified are produced by the Aramis SRX system.

Next measurement data is conveyed through three cables located at the rear of the measuring bar. This data is subsequently processed using the manufacturer’s software, resulting in the creation of a file that contains the measurement data. Initially, this file is temporarily saved on the GOM PC’s hard drive before being transferred to the network drive. To accomplish this, the data must be retransmitted via an Ethernet cable linked to the GOM PC.

Finally, the data is stored on the network drive, ensuring that all computers can access and further process the measurement data.

Another crucial factor is interference, which pertains to influences that could damage or distort the measurement data. Errors are particularly likely during data transmission through the cables, which have connectors at each end that can present additional risks if mishandled. Examples include cable breaks that render data transmission impossible, and the breakage of one or more of the delicate pins in the connectors, which can also hinder accurate data transmission. Additionally, strong magnetic fields can disrupt the transmission of measurement data.

In this study, a limited number of errors from the test bench

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were selected. From these, an appropriate algorithm has been developed to identify these anomalies and promptly repeat the related measurements. To create and ultimately test this algorithm, erroneous measurement data is necessary, which was supplied by the test bench team. All evaluated errors stemmed from malfunctions of the Aramis-SRX.

There are several possible causes for this issue. One possibility is a failure in the data transfer from Aramis to the control computer in the control room, resulting in the data being unavailable. Another scenario could be an error in the naming of individual channels on the Aramis computer. If the script intended to create the MAT file is supposed to generate it from the tables sent, it may not find a channel with the specified name and leave it blank.

To detect such missing entries, one method is to compare the actual name with a pre-established list of target names. If the name is found, the program can proceed. If not, corrective actions must be taken.

A common issue that can arise is the absence of data points, which manifest as voids in the graph and, if too numerous, can make the measurement invalid.

Figure 4 serves as an illustration of this problem. A detailed examination of the wheel center's displacement diagram in the X direction over time reveals missing points for the FL (front left). This issue persists in the diagram showing displacement relative to force in the X direction over time, it is noticeable that some points are missing for FL (front left). This is also reflected in the diagram showing the displacement over the force in the X direction. These voids are typically produced by the Aramis system when one or more measurement points are no longer detected. This can be caused by a software glitch, damage to the reflective surfaces of the points, or vehicle movement due to input from the test bench. Such gaps may also occur during the creation of the MAT file when synchronization or upsampling is conducted, leading to unfeasible operations during this process, and Matlab inserts 'NaN' values at these locations.

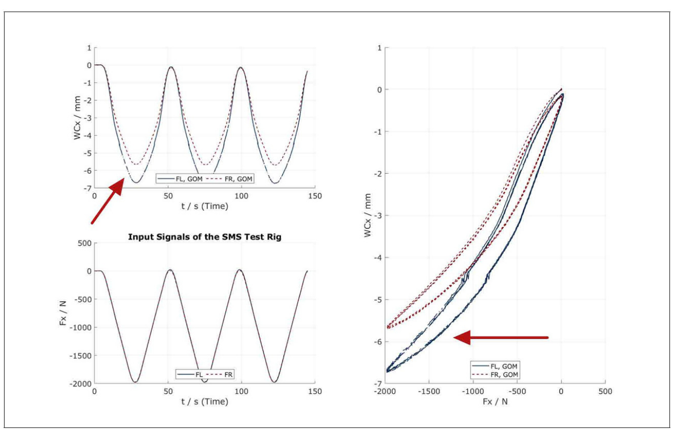

Figure 4. Plotted measurement data from a T04 with errors in the front left data. On closer inspection of the diagram showing the wheel centre displacement in the X direction over time.

There are several methods to identify and correct such errors, see the following explanations. An attempt was made to process the measurement data using both high-pass and low-pass filters. However, because the jumps did not occur at a specific frequency, this approach was ineffective. A median filter was also applied, but it failed to deliver the desired results with the substantial jumps observed here. Consequently, the idea of filtering the measurement data to eliminate jumps was abandoned. Another method to detect the jumps is to remove points that deviate from the mean value by a certain percentage. Additionally, there is the option of calculating the difference between consecutive points and setting a threshold value for this.

An additional error that may arise pertains to the noise levels in the various measurement channels. The noise levels of the signals on the left and right sides differ. This discrepancy can result from external factors during data transmission or from inaccuracies in recording the measurement data. Figure 5 illustrates an example of this error pattern. In the top left diagram, which depicts the wheel center displacement in the Y direction over time, the left side exhibits a highly noisy signal. Conversely, the right side's signal is much clearer. This difference is also apparent in the diagram showing the wheel center displacement in the Y direction over force, where a significantly larger amplitude is noticeable on the vehicle's left side.

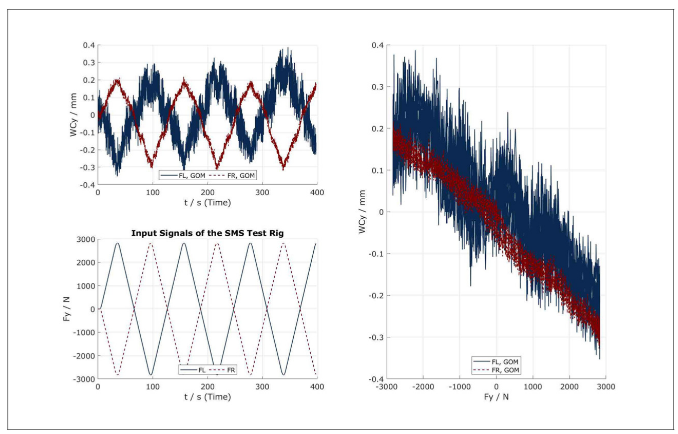

Figure 5. Plotted measurement data from a T03 with channels of varying noise levels for wheel centre displacement in the Z direction.

To assess the noise levels in the measurement data, Fourier analysis is employed. This technique allows for the plotting of amplitude against frequency, enabling insights into the various components. By comparing the data obtained through this method, it becomes evident whether the channels on the left and right sides exhibit different noise levels.

The algorithm's first task is to verify completeness, ensuring all channels are present and the measurement data is free of NaN values (erroneous values). The program should terminate if a channel is absent or if the number of missing values surpasses a certain threshold. Although checking for NaN values was initially intended as a separate step, it was found more practical to incorporate it into the first step during programming. In the second step, the measurement data is examined for jumps, which are values so implausible that they are considered measurement errors.

Such measurements can skew the overall outcome and need to be identified or, if necessary, eliminated. If this cannot be done, the measurement should be conducted again. In the subsequent step, the data is examined to assess the level of noise and to check for significant discrepancies in this aspect. If the LF side channel is considerably noisier than the RF side, the measurement should be redone.

As per the diagram, the first requirement is the generated MAT file. This file, along with structures, such as GOM, Bank GOM, and Bank MTS, among others, is imported by the main program, as they are essential for the verification process. Subsequently, a pre-existing list that includes all approved names for the various GOM channels is loaded. The significant advantage of this list is its ability to be updated at any time without necessitating code modifications. Therefore, if a new channel needs to be added or a name change is required in the future, it can be done with minimal effort.

D. Mathematical background of the individual methods

The Fourier analysis tool is essential for identifying the different frequencies present in the noise. However, the exact method for making the comparison still needs to be developed. The next section aims to explain the approaches that will be implemented in the program code. Initially, a channel was selected from the measurement data that exhibited a significant noise difference between the left and right sides. This data represented the wheel center's displacement in the X direction over time. It was thoroughly analyzed, and a Fourier analysis was conducted to identify the various dominant frequency components and their amplitudes.

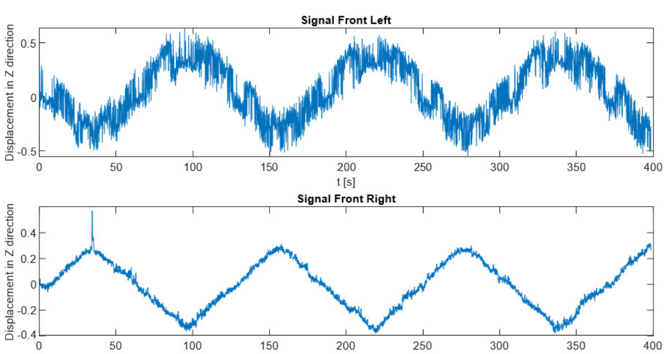

Figure 6. Signal from the left and right sides with strong channel noise.

Figure 6 presents the data for the Front Left and Front Right of the chosen channel, illustrating the wheel center's movement in the Z direction. It is evident that the Front Left exhibits considerably more noise compared to the Front Right. Theoretically, this implies that the amplitudes on the left side should be higher than those on the right side in the frequency ranges where the noise occurs.

Conducting a Fourier analysis on the aforementioned channel verifies the hypothesis that amplitude variations exist across different frequencies. There is a noticeable increase in amplitude for frequencies up to 10 hertz. The initial peak is insignificant, as it represents the very slow fundamental oscillation of the signal. Consequently, only frequencies above roughly 1 Hz are pertinent to these considerations.

By utilizing these insights, one can determine the average value from the dataset generated by diff() and subsequently compare the values for both sides. Additionally, the percentage difference between the two channels can be calculated, and an alert can be issued if the discrepancy is excessively large.

NaN in MATLAB stands for "Not a Number" - it is a special floating-point value that represents undefined or unrepresentable numerical results. Common Causes of NaN:

NaN values often indicate:

- Sensor malfunction or disconnection
- Data transmission errors
- Out-of-range measurements
- Calibration failures
- Signal processing errors

The measurement data, now devoid of NaN values, is assigned to a new variable. An array of the same length as the measurement data is generated, containing only zeros and ones. A one indicates where interpolation has occurred. The count of interpolated values is then determined and recorded in a table for reference. In this scenario, the missing measurement data is interpolated using a linear method.

This section brings up another crucial issue: how should one handle measurement data with excessive missing values? To address this, a query was integrated into the main script. It utilizes the calculated number of NaN values from the completeness check function to terminate the program once the percentage hits 17%. Beyond this percentage, linear interpolation issues may arise if the missing values are located at specific points, such as the peaks and troughs of the measurement data. The situation worsens if they are concentrated in a single area.

The subsequent step involves executing the Fourier transform using the fft() function. The algorithm's calculations and the individual steps for executing them were sourced from the Matlab help (MathWorks, 2022) and tailored to meet the requirements.

A Fourier transform is conducted for both channels at the same time, as they need to be compared. Additionally, the amplitude is normalized, which does not affect the results since it is applied to both sides. Moreover, the spectrum must be adjusted, and the frequency array calculated. This is performed following the example on the Matlab help page (MathWorks, 2022).

Following this, a condition is applied to identify the position of the 1 Hz frequency. This value is used to eliminate all amplitudes before the frequency and to ascertain the difference between the remaining values, providing their amplitudes. The mean of the absolute values is then computed to determine their dimensions.

The process involves first identifying the larger mean value and then dividing it by the smaller mean value, utilizing an if condition to achieve this. The resulting value is subsequently recorded in the results table and displayed as output.

V. Outline of the results

In the following, the results are outlined, the advantages and disadvantages of the proposed solution are discussed and some of the areas in which it is applicable are given.

The objective of this scientific study, which was to develop a functional algorithm for identifying a range of errors on the Suspension Motion Simulator, has been accomplished. Additionally, a concept has been devised to enable future expansion of the program to identify more errors. The algorithm created here allows for an initial diagnosis of the data in real-time or during measurement and can be repeated if an error occurs. The algorithm is adaptable to the tests conducted through extensive parameterization, which, among other things, facilitates highly accurate jump detection.

An important benefit of the developed algorithm is its versatility across various data sets, along with the ability to manage dynamic measurements, as long as they fulfill the required criteria. Additionally, the inclusion of multiple editable lists facilitates the enhancement of the algorithm's capabilities. Should future modifications to the different channels be needed, they can be easily incorporated by updating these lists. This establishes a robust basis for creating a database with accurate measurement data or for later eliminating flawed data sets. Consequently, we can continue to pursue the objective of integrating machine learning into test bench evaluation. Moreover, the evaluation process now requires less time, allowing us to use this time to, for instance, redo incorrect measurements. This also helps achieve the aim of cutting costs and easing the workload of the test bench team and clients.

To summarize, the paper's primary contributions include the creation of effective algorithms for edge computing platforms that assess sensor data quality during production processes. This is achieved through a structured methodology, exemplified by the Suspension Motion Simulator case study, which validates methods for enhancing sensor quality using quantifiable performance metrics. The research posits that unified quality assessment strategies can adeptly manage various sensor technologies from different manufacturers, each with distinct protocols and data formats, and that sensor errors exhibit identifiable patterns detectable through mathematical techniques such as Fourier analysis and statistical thresholds. However, the approach has some limitations; the validation is mainly centered on errors in the Aramis SRX optical measurement system, which may not fully represent the range of sensor failures in diverse CPPS environments. Despite the automation objectives, the system still necessitates human oversight for decisions regarding measurement repetition. Additionally, the paper does not thoroughly explore the challenges of integrating with existing industrial monitoring systems beyond basic compatibility.

VI. Conclusion and future work

This study has effectively created and confirmed detailed methods to enhance the quality of sensor data in CPPS, including error detection by utilizing digitalization technologies. The structured framework offered tackles essential issues in contemporary manufacturing settings by merging cutting-edge digital technologies with practical implementation factors. The newly developed methodology showcases notable advancements in sensor reliability by employing real-time quality assessment algorithms, multi-modal error detection capabilities, and smooth integration with current production infrastructures. The Suspension Motion Simulator case study confirms the practical effectiveness of these methods, demonstrating significant improvements in the accuracy of sensor fault detection and a decrease in false alarm rates. The framework's modular design allows for scalable deployment across various manufacturing settings while maintaining computational efficiency suitable for edge computing platforms.

There are numerous promising avenues that warrant further investigation. To begin with, the fusion of artificial intelligence and large language models offers transformative possibilities for managing sensor data quality. Foundation models, pre-trained on a variety of sensor datasets, could deliver universal anomaly detection capabilities across diverse sensor networks, while transformer-based architectures might capture intricate temporal dependencies in sensor time-series data that traditional methods overlook. Large language models could automate the creation of sensor maintenance documentation, translate complex sensor anomalies into human-readable diagnostic reports, and offer conversational interfaces for interactive sensor troubleshooting. The foundation established by this research provides a robust platform for continued advancement in sensor data quality management, positioning manufacturers to leverage digitalization technologies for enhanced production reliability and competitiveness in Industry 4.0 environments.

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