AIoT-enabled decentralized sensor fault diagnosis for structural health monitoring

Carlos Chillón Geck, Thamer Al-Zuriqat, Moayed Elmoursi, Kosmas Dragos, and Kay Smarsly
Institute of Digital and Autonomous Construction, Hamburg University of Technology, Germany, carlos.chillon.geck@tuhh.de

Abstract. Artificial intelligence (AI) algorithms have proven effective in implementing sensor fault diagnosis (FD) for wireless structural health monitoring (SHM). However, FD models based on AI are computationally expensive and require large amounts of raw sensor data to be transmitted to centralized servers. This paper proposes a decentralized framework for sensor fault diagnosis in wireless SHM systems based on the concept of Artificial Intelligence of Things (AIoT). Within the decentralized framework, FD models are embedded into wireless sensor nodes to ensure that the data collected from engineering structures is fault-free. Thus, only the condition of SHM systems, instead of raw data, is transmitted from SHM systems to centralized servers via Internet-of-Things communication. To validate the decentralized framework proposed in this paper, an SHM system is implemented using (i) a portable main station containing the FD models and (ii) four tailor-made wireless sensor nodes equipped with microcontrollers and accelerometers deployed on a test structure. The results of the validation tests show that the SHM system successfully collects acceleration data and diagnoses, in real-time, sensor faults that are inserted into the sensor nodes. In future work, the decentralized framework and the SHM system presented in this paper may be deployed on a bridge for structural condition assessment, while ensuring early detection of sensor faults.

Keywords: Structural health monitoring (SHM); Internet of Things (IoT); Artificial Intelligence of Things (AIoT); sensor fault diagnosis.

1. Introduction

Advanced sensor technologies have extensively been applied in structural health monitoring (SHM) [1]. SHM systems may include accelerometers [2], fiber optic sensors [3], embedded temperature sensors [4], or mobile sensing devices, such as unmanned aerial vehicles [5] or legged robots [6]. Wireless SHM systems have become particularly popular due to the low installation costs and reduced installation time as well as the potential of scalability, compared to conventional wired systems [7]. The reliability and performance of wireless SHM systems depend on the quality of the data collected by the sensors. However, sensors may malfunction over time or experience data transmission problems, impeding correct structural assessment [8].

Developments in artificial intelligence (AI) and Internet of Things (IoT) technologies have substantially enhanced the ability of wireless SHM systems to monitor and assess structural conditions, improving maintenance activities towards safer and more resilient civil infrastructure [9]. To minimize the impact of faulty sensor data, different sensor fault diagnosis (FD) approaches have been proposed in several engineering disciplines [10], including SHM [11]. In the field of wireless SHM in particular, AI and signal processing techniques have been applied to detect and identify sensor faults [12]. Furthermore, a sensor FD approach based on artificial neural networks has been proposed using structural response data in the frequency domain [13]. In [14], artificial neural network (ANN) models have been proposed to detect simultaneous sensor faults. Nonetheless, sensor FD approaches for wireless SHM systems are usually not implemented into the sensor nodes, but typically run on centralized servers, thus preventing real-time sensor data visualization, storage, and remote interaction with SHM systems.

This paper aims to address the current shortcomings using the Artificial Intelligence of Things (AIoT) paradigm, which integrates artificial intelligence with Internet of Things technologies [15], providing opportunities to exploit the increasing computational capacity of embedded devices, such as sensor nodes present in wireless SHM systems. Embedded computing avoids bandwidth limitations by transmitting a few of information instead of transmitting large amounts of raw data, thus representing a promising feature of modern SHM systems. This paper presents an AIoT-enabled, decentralized sensor fault diagnosis (DSFD) framework, consisting of (i) embedded AI models for sensor FD and (ii) information transmission capabilities using IoT technologies facilitating real-time data visualization, data storage, and interact with SHM systems. The DSDF framework is implemented on a tailor-made wireless SHM system consisting of (i) sensor nodes, each including a microcontroller and an accelerometer, and (ii) a portable main station with embedded FD models. The remainder of the paper is structured as follows. First, the DSFD framework, focusing on the sensor FD models, and the development of the wireless SHM system are elucidated in Section 2. In Section 3, the validation of the DSFD framework, conducted by inserting artificial sensor faults into acceleration data, are presented and the validation results are discussed. Finally, Section 4 summarizes the paper, giving an outlook on potential future applications and possible improvements of the wireless SHM system.

2. A decentralized sensor fault diagnosis framework for structural health monitoring

This section presents the AIoT-enabled, decentralized sensor fault diagnosis framework, which builds upon the "adaptive FD based on analytical redundancy" (AFDAR) approach, as proposed by the authors in [14]. Thereupon, the development of a wireless SHM system, implementing the DSFD framework based on a layered IoT architecture, is described.

2.1 Decentralized sensor fault diagnosis

The AFDAR approach serving as a conceptual basis for the DSFD framework uses artificial neural networks and signal processing to create AI-based FD models, specifically ANN models, for detecting patterns of common sensor faults in sensor data. Sensor faults that commonly occur in SHM systems include complete failure, complete failure with noise, outliers, drift, bias, and gain. Once a sensor fault is detected, the faulty sensor data is replaced with virtual sensor data predicted by the ANN models. In three steps, the AFDAR approach detects, isolates, and accommodates sensor faults, as depicted in the process diagram shown in Fig. 1:

- *Fault detection*, which recognizes an adverse operation of the SHM system.
- *Fault isolation*, which specifies the exact location of a fault.
- *Fault accommodation*, which compensates for the effects of the fault.

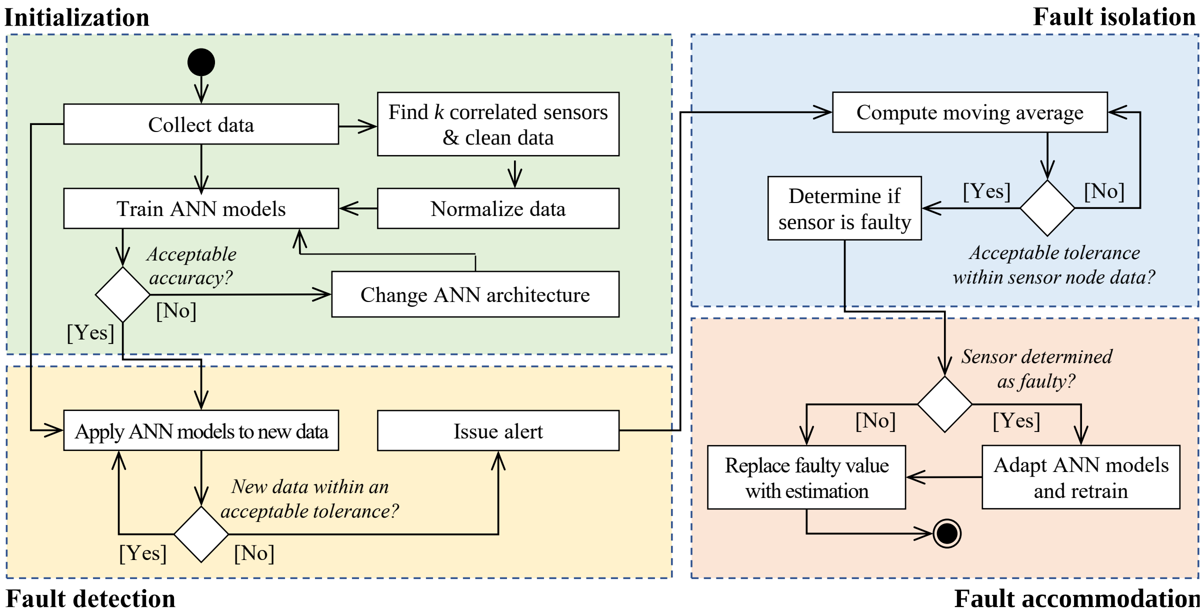

Fig. 1. Process diagram of the AFDAR approach serving as a conceptual basis of the DSFD framework

2.2 Development of a wireless SHM system based on AIoT

The wireless SHM system developed in this work is based on a four-layer IoT architecture that includes the following four layers, shown in Fig. 2.

- *Physical layer*, which includes the actual hardware components, i.e. microcontrollers and sensors, to collect data, process data with embedded computing, and transmit information between devices with IoT communication protocols.
- *Middleware layer*, which facilitates database management and communication between the different applications and services of the SHM system and embeds the FD models.
- *Application layer*, which provides an interface that allows end users to interact with the SHM system, e.g. via a dashboard and a control panel.
- *Security layer*, which encompasses measures implemented transversely across various layers to protect sensor data and communication. The measures include encryption, authentication, and access control methods at different layers.

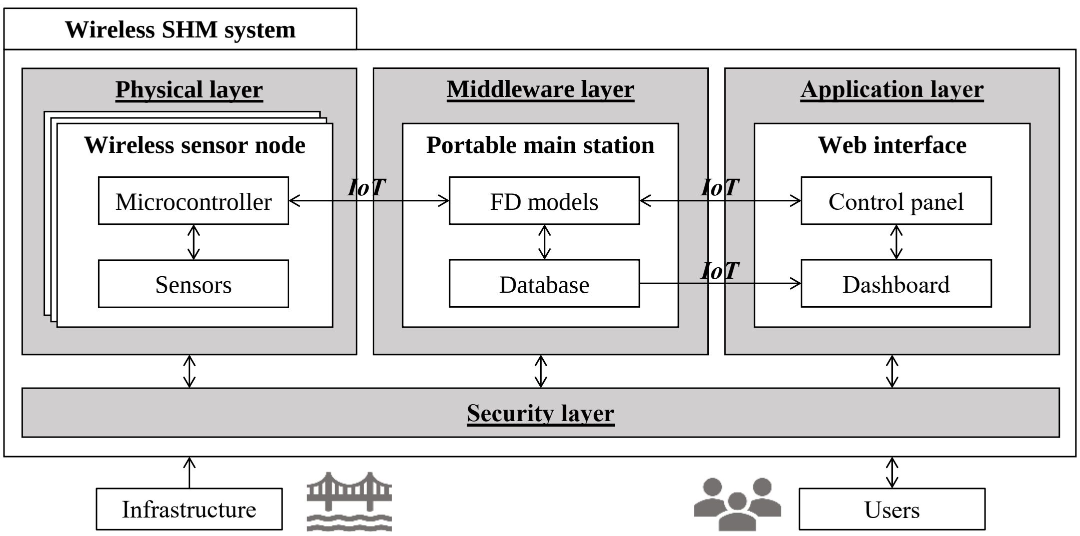

Fig. 2. Architecture of the wireless SHM system for decentralized FD

The four layers are implemented as follows. The physical layer comprises sensor nodes consisting of off-the-shelf, low-cost hardware components, including microcontrollers, sensors, and small electrical components, such as transistors, resistors, and capacitors. Each sensor node includes (i) an accelerometer of type BNO085 and (ii) an environmental sensor of type BME280, both from Adafruit. The sensors are connected to a microcontroller of type ESP32-S3 from Espressif. The components are selected according to affordability, IoT compatibility, compactness, and adherence to open-source principles. Fig. 3 shows the PCB board designed to connect the hardware components and the view of the sensor node, after assembly and integration into an enclosure.

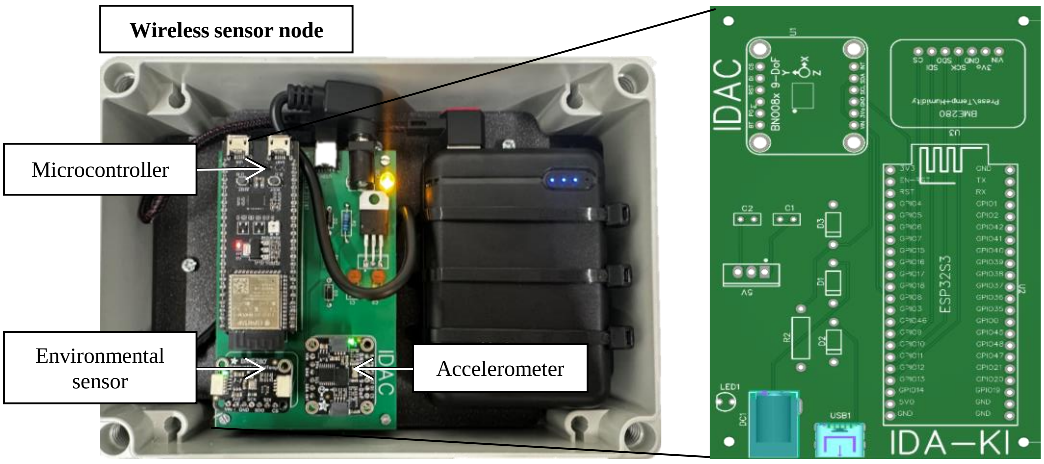

Fig. 3. Wirless sensor node for SHM

The middleware layer consists of a Raspberry Pi, serving as a portable main station that provides two main services, (i) bidirectional data transmission between the devices and (ii) data management and storage. Data transmission is handled by Node-RED and the lightweight IoT communication protocol termed “message queuing telemetry transport” (MQTT). An MQTT server is implemented to handle, on the one hand, the sensor data received from the sensor nodes and, on the other hand, the queries entered by the users to interact with the SHM system. The MQTT communication is based on a publish-and-subscribe protocol designed for IoT applications. Data management and storage is handled by Telegraf, which receives the sensor data from the MQTT server and stores the data in a highly efficient manner to a time-series database implemented with InfluxDB. The communication among the components of the middleware layer as well as the communication between the wireless sensor node (physical layer) and the middleware layer are illustrated in Fig. 4.

The application layer features a website, created by Node-RED from the middleware layer, that includes an interface with a control panel and a dashboard for data visualization. The control panel allows users to communicate with the sensor nodes via MQTT for setting sampling rates and durations of the data collection process. In addition, the dashboard displays sensor data in real time and shows alerts when the FD models embedded in the portable main station detect faulty sensors. The website is physically hosted at the portable main station, and users with authentication rights have remote access to both the control panel and the dashboard from any end device.

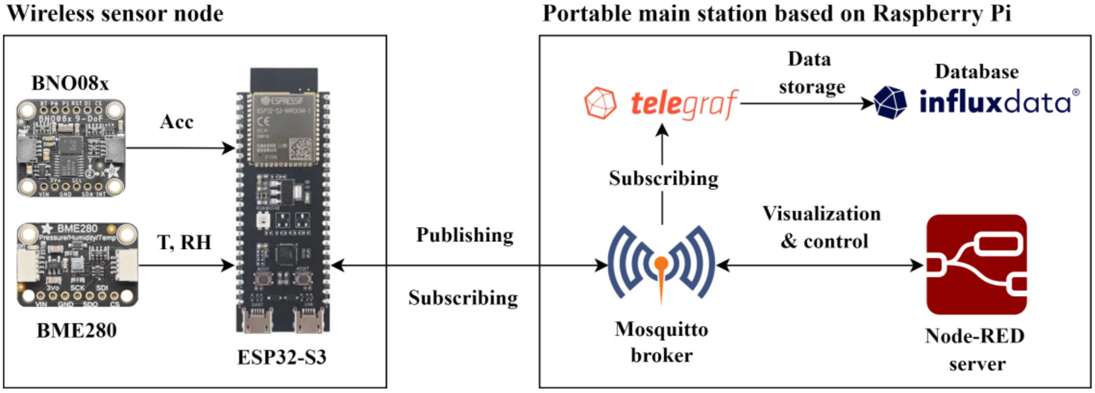

Fig. 4. Communication schema between sensor nodes and portable main station

Finally, the security layer includes authentication methods, based on user names and passwords, to access the components of the SHM system. All components are connected to a private wireless local network. The wireless SHM system implemented herein, based on the Artificial Intelligence of Things for decentralized sensor FD, is validated in a laboratory test, which is described in the next section.

3. Validation of the decentralized sensor fault diagnosis framework

The decentralized sensor fault diagnosis framework is validated by installing the SHM system on a test structure. The test setup and the results of the test are described in this section. Noticeably, the SHM system serving for validation purposes consists of four sensor nodes and a portable main station, forming a hierarchical cluster.

3.1 Test setup

The test setup is shown in Fig. 5. Four wireless sensor nodes (WSN1, WSN2, WSN3, WSN4) are deployed on a metallic shear-frame structure with dimensions 60 cm × 18 cm × 13 cm (height, width, depth). The test structure is placed on a shake table consisting of a plate, a stepper motor, and a microcontroller capable of regulating the amplitude and the frequency of the excitation remotely via IoT technologies [16].

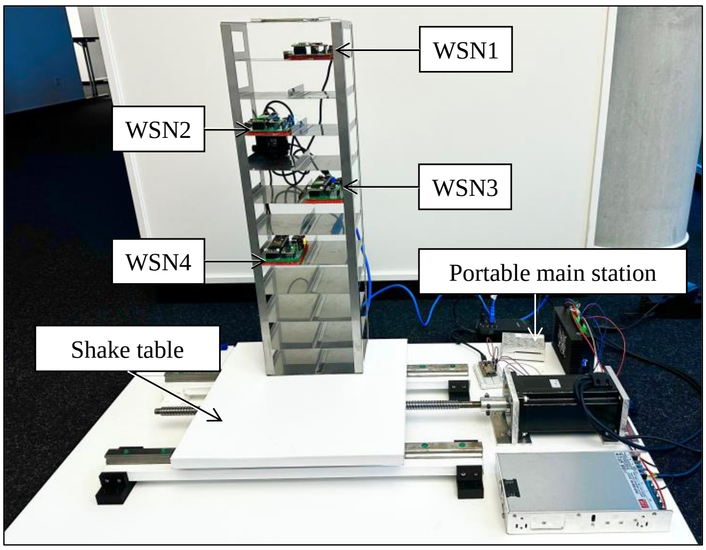

Fig. 5. Test setup for the validation of the fault diagnosis

The validation test is conducted following six steps.

1. *Data collection*: Acceleration data is collected for 2 hours, including “forced vibration” (when the shake table is actively applying force/motion to the structure) and “free vibration” (when the shake table is not applying motion). The microcontroller of the shake table induces a unidirectional excitation to the shake table of 5 Hz with an amplitude of 1 cm. The sampling rate of the sensor nodes is set to 100 Hz, which generates 720,000 measurements per sensor node for training the AI models for FD.
2. *Training of FD models*: The sensor data collected in step 1 is used to create AI-based FD models, one for each sensor node. From the data, 70 % is dedicated to training, 20 % to validation, and 10 % to testing. In this step, the AI-based FD models “learn” how sensors measure when there are no faults present in the wireless SHM system.
3. *Embedding FD models*: The trained FD models are embedded into the portable main station of the wireless SHM system and integrated into a script that runs automatically.
4. *Collection of new data*: The sensor nodes collect new data, which is sent via MQTT to the main station. The new sensor data is used as an input to the FD models, which assess the state of the sensors, i.e. faulty or non-faulty.
5. *Insertion of sensor faults*: To validate that the DSFD framework diagnoses sensor faults in real-time, two types of sensor faults are inserted into the SHM system. First, a bias sensor fault is artificially inserted by adding a constant value of 2 to the actual measurements of the accelerometer of WSN1. Second, a complete failure of a sensor is simulated by unplugging the accelerometer of WSN1.
6. *Validation of real-time FD*: Upon inserting the sensor faults, users receive the alert sent by the system to the dashboard of the web application.

3.2 Results of the test

The results of the test are illustrated in Fig. 6, illustrating the measurements of the *y*-axis (the axis where forced vibration is induced by the shake table) of the accelerometers of the wireless sensor nodes (labeled “WSN1y”, “WSN2y”, “WSN3y”, and “WSN4y”). The first minute of the test (first phase) occurs under normal working conditions of all wireless sensor nodes. During normal working conditions, the control panel displays a green light for every measurement of the sensor nodes. During the second minute of the test, the bias fault is inserted in the *y*-axis of WSN1.

As a result of applying sensor FD, a red light flashes in the control panel, indicating that a sensor fault has been detected. Next, the SHM system isolates the sensor fault. During the third minute of the test, the sensor faults are removed and normal working conditions are restored in the system. The normal working conditions are represented in the control panel by displaying green lights. Finally, in the fourth minute of the test, a red light flashes for all axis of WSN1, i.e. x-, y-, and z-axis, as result of a complete failure of WSN1, simulated by unplugging the accelerometer of WSN1.

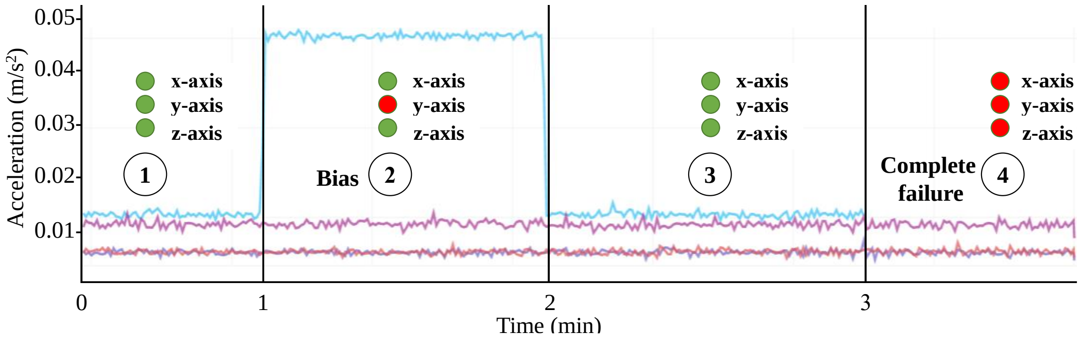

Fig. 6. Results of the real-time FD

3.3 Discussion of the results

The results of the validation test confirm that the decentralized sensor fault diagnosis framework is capable of diagnosing sensor faults in real time. When a sensor fault is detected, the SHM system sends an alert to notify that a specific sensor has been classified as faulty. Thus, maintenance activities can be conducted quickly, reducing the loss of data and, by extension, ensuring reliable structural health assessment. The real-time diagnosis of sensor faults is conducted directly on the structure ("edge computing") by means of the portable main station, which receives data from the wireless sensor nodes and applies the FD models based on AI, avoiding sending raw data to a centralized server for analysis.

By using IoT-based off-the shelf hardware components and open-source software, the system can scale to large structures with multiple hierarchical clusters of wireless sensor nodes and portable main stations, while keeping the implementation cost low. However, the portable main station based on Raspberry Pi, faces computational limitations when training AI models onboard. During the validation test, acceleration data has been used to train the AI-based FD models "offline", and only the trained FD models run on the main station. To conduct the training of the FD models onboard of the main station, either (i) a computationally more powerful portable computer may be used, or (ii) the AI-based FD models may be optimized for embedded, portable computers. Solving one of the two limitations when training the FD models would fully decentralize FD assessment, representing potential future work.

Summary and conclusions

Considering the increasing trends in digitalization and the advances in AI and IoT technologies, wireless SHM is expected to draw from the technological advancements to improve the reliability and longevity of infrastructure. To this end, this paper has presented an AIoT-enabled decentralized sensor fault diagnosis framework to assess the state of wireless SHM systems by detecting, isolating, and accommodating sensor faults in a decentralized fashion. The test results clearly demonstrate the feasibility of the DSFD framework, highlighting the advantages of the proposed approach, including real-time FD avoiding the transmission of raw data to centralized servers, and opportunities to scale SHM systems at low implementation and installation costs. In addition, the DSFD framework enables real-time data visualization, data storage, and remote interaction with the SHM system. In future work, the SHM system may be augmented by increasing the number of clusters of wireless sensor nodes and portable main stations to be deployed on a large-scale testing bridge [17], to demonstrate the capability of the DSFD framework in real-world conditions. Furthermore, improvements of the DSFD framework may focus on adding a fault identification algorithm to classify the type of sensor fault, and on replacing the current hardware with more computationally powerful components to train FD models directly onboard of portable main stations.

Acknowledgements

The authors would like to express their sincere gratitude for the generous support received from the German Research Foundation (DFG) under grant SM 281/17-1, by the German Federal Ministry for Digital and Transport (BMDV) within the mFUND program under grant 19FS2013B, and by the German Federal Ministry of Health (BMG) under grant 910003. Any opinions, findings, conclusions, or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the sponsors.

References

[1] S. Hassani & U. Dackermann, 2023. A Systematic Review of Advanced Sensor Technologies for Non-Destructive Testing and Structural Health Monitoring. Sensors, 23(4), 4.
[2] A. S. Azhar, S. A. Kudus, A. Jamadin, N. K. Mustaffa, & K. Sugiura, 2024. Recent vibration-based structural health monitoring on steel bridges: Systematic literature review. Ain Shams Engineering Journal, 15(3), 102501.
[3] M. Herbers, B. Richter, D. Gebauer, M. Classen, & S. Marx, 2023. Crack monitoring on concrete structures: Comparison of various distributed fiber optic sensors with digital image correlation method. Structural Concrete, 24(5), pp. 6123-6140.
[4] T. Al-Zuriqat, C. Chillón Geck, K. Dragos, & K. Smarsly, 2023. Diagnosis of simultaneous sensor faults in structural health monitoring systems. In: Proceedings of the European Council on Computing in Construction Conference (EC3). Heraklion, Greece, 07/12/2023.
[5] S. Sony, S. Laventure, & A. Sadhu, 2019. A literature review of next-generation smart sensing technology in structural health monitoring. Structural Control Health Monitoring, 26(3), e2321.
[6] K. Smarsly, K. Dragos, J. Stührenberg, & M. Worm, 2023. Mobile structural health monitoring based on legged robots. Infrastructures, 8(9), 136.
[7] P. Ragam & N. D. Sahebraoji, 2019. Application of MEMS-based accelerometer wireless sensor systems for monitoring of blast-induced ground vibration and structural health: A review. In: IET Wireless Sensor Systems, 9(3), pp. 103-109.
[8] R. R. Swain, T. Dash, & P. M. Khilar, 2022. Automated Fault Diagnosis in Wireless Sensor Networks: A Comprehensive Survey. Wireless Personal Communications, 127 (4), pp. 3211-3243.
[9] A. Malekloo, E. Ozer, M. AlHamaydeh, & M. Girolami, 2022. Machine learning and structural health monitoring overview with emerging technology and high-dimensional data source highlights. Structural Health Monitoring, 21(4), pp. 1906-1955.
[10] Z. Zhang, A. Mehmood, L. Shu, Z. Huo, Y. Zhang, & M. Mukherjee, 2018. A Survey on Fault Diagnosis in Wireless Sensor Networks. IEEE Access, 6(2018), pp. 11349-11364.
[11] K. Smarsly & K. H. Law, 2014. Decentralized fault detection and isolation in wireless structural health monitoring systems using analytical redundancy. Advances in Engineering Software, 73(2014), pp. 1-10.
[12] H. Fritz, J. J. Peralta Abadía, D. Legatiuk, M. Steiner, K. Dragos, & K. Smarsly, 2022. Fault Diagnosis in Structural Health Monitoring Systems Using Signal Processing and Machine Learning Techniques. In: Structural Health Monitoring Based on Data Science Techniques, A. Cury, D. Ribeiro, F. Ubertini, and M. D. Todd, Eds., in Structural Integrity. Cham: Springer International Publishing, Switzerland, pp. 143-164.
[13] K. Dragos & K. Smarsly, 2016. Distributed adaptive diagnosis of sensor faults using structural response data. Smart Material Structures, 25(10), 105019.
[14] T. Al-Zuriqat, C. Chillón Geck, K. Dragos, & K. Smarsly, 2023. Adaptive Fault Diagnosis for Simultaneous Sensor Faults in Structural Health Monitoring Systems. Infrastructures, 8(3), 39.
[15] J. Zhang & D. Tao, 2021. Empowering Things with Intelligence: A Survey of the Progress, Challenges, and Opportunities in Artificial Intelligence of Things. IEEE Internet of Things, 8 (10), pp. 7789-7817
[16] Al-Zuriqat, T., Peralta, P., Chillón Geck, C., Dragos, K., & Smarsly, K., 2023. Implementation and validation of a low-cost IoT-enabled shake table system. In: Proceedings of the 14th International Workshop on Structural Health Monitoring (IWSHM). Stanford, CA, USA, 09/12/2023.
[17] M. Herbers., J.-H. Bartels, B. Richter, F. Collin, L. Ulbrich, T. Al-Zuriqat, C. Chillón Geck, H. Naraniecki, O. Hahn, F. Jesse, K. Smarsly, & S. Marx, 2024. openLAB – A research bridge for developing a digital twin of bridges [openLAB – Eine Forschungsbrücke zur Entwicklung eines digitalen Brückenzwillings]. Beton- und Stahlbetonbau, 119(3), pp. 169-180.