Dynamic Monitoring of Bridge Structures via an Integrated Cloud and Edge Computing System

Guoqi Zhang[1], Pengcheng Zhang[2], Xingwang Li[3], Yizhe Yang[4]*
China First Highway Engineering CO., LTD., Beijing 100024, China[1, 2, 3]
College of Civil Engineering, Xuchang University, Xuchang 461000, China[4]

***Abstract*—Traditional bridge monitoring techniques, which predominantly rely on centralized data processing, often exhibit slow and inflexible responses when managing large-scale sensor network data. This study proposes an integrated edge and cloud computing approach to enhance the response time and data processing efficiency of dynamic bridge structure monitoring systems, thereby improving bridge safety and reliability. The proposed monitoring system leverages both edge and cloud computing, incorporating modules such as sensor data management, structural assessment and warning, data processing, monitoring, and data acquisition and transmission. High-performance and cost-effective sensors are utilized to monitor the real-time dynamic responses of the bridge, including displacement, acceleration, tilt, and stress, as well as external loads and environmental effects. The data processing module employs the modal superposition method, frequency response function, and modal analysis for dynamic analysis, while the cloud computing platform facilitates deep learning analysis and long-term data storage. A real case study demonstrates the system's performance across various settings and operational conditions, highlighting the effectiveness of integrating edge and cloud computing. The results indicate that the integration scheme significantly enhances monitoring accuracy, system stability, real-time response capacity, and data processing efficiency.**

Keywords*—*Dynamic monitoring of bridge structures; edge computing; cloud computing; data processing; modal analysis

I. Introduction

As the world's infrastructure ages faster and bridge loads continue to climb, maintaining the durability and safety of bridge structures has become increasingly important for transportation infrastructure managers. Bridges are essential transportation hubs, and public safety and economic prosperity are directly impacted by the state of these structures. Consequently, the importance of monitoring and evaluating bridge health has increased. Recent developments in data collection, processing, and sensing technologies have made dynamic monitoring of bridge structures a hot topic for study. However, a number of challenges face traditional bridge monitoring techniques, including real-time data processing, system adaptability, and data security.

In order to anticipate future failures and safety risks, the goal of health monitoring bridge structures is to gather and evaluate the structural response of bridges in real time. Conventional monitoring techniques typically depend on centralized data processing systems, which frequently experience issues with massive amounts of data, including processing delays, bandwidth bottlenecks, and data loss [1]. Bridge monitoring systems can now collect vast amounts of high-frequency data due to advancements in sensor technology, which place more demands on data processing. Complex sensor data must be processed in real time in modern bridge monitoring in order to assess the structural response of the bridge, identify possible issues, and promptly take corrective action [2]. Thus, it is now a top research priority to investigate new monitoring schemes to guarantee data confidentiality, boost system adaptability, and increase data processing skills.

Many existing structural health monitoring (SHM) systems use traditional wired sensor networks, which are prone to scalability problems. As the number of sensors increases, the complexity of wiring and maintenance grows, leading to higher costs and greater difficulty in system management. Wireless sensor networks (WSNs) have been introduced to address some of these issues, but even WSNs face challenges in terms of signal interference, data loss, and power consumption, especially in large-scale infrastructure like long-span bridges.

While numerous systems claim to offer real-time monitoring, their data processing speeds and transmission methods often lag behind the real-time requirements of critical infrastructures. Most systems are not equipped to handle the massive influx of data generated by high-frequency sampling from multiple sensors, leading to delays in data processing and reporting. Furthermore, interruptions in data transmission due to connectivity issues often result in incomplete or delayed data analysis, making it difficult to monitor structural health accurately in real time.

One major limitation of existing SHM systems is the lack of robust fault tolerance mechanisms. Many systems do not have adequate backup solutions in place to prevent data loss during network outages or hardware failures. The absence of local storage for sensor data during communication interruptions can lead to significant gaps in monitoring, especially during critical events such as natural disasters or severe weather conditions. This undermines the reliability of the data collected and the system's ability to provide timely alerts.

Most traditional SHM systems rely on basic statistical methods for evaluating structural health. While these methods are useful for analyzing deformation, vibration, and load responses, they often fail to provide accurate predictions or insights into long-term structural behavior. The integration of intelligent algorithms such as machine learning, which could predict potential failure points or structural degradation based on historical data, remains underexplored in many existing solutions.

*Corresponding Author

Large volumes of data are produced by bridge monitoring systems, particularly when high frequency sampling is used. Conventional centralized data processing techniques are frequently unable to keep up with the needs of real-time processing [3]. Due to this, data is delayed and any structural anomalies or early warning signals may go unnoticed. Although edge computing, which processes data in real time close to the site of collection, can significantly cut down on transmission delays, it has drawbacks in terms of deep analysis and storage capacity [4, 5]. It is necessary to prevent and address potential security breaches, system malfunctions, and data loss during data transmission and storage with appropriate methods. Temperature, wind speed, traffic volume, and other climatic and operational variables can all have an impact on a bridge's structural response. In order to guarantee the precision and dependability of the monitoring data under diverse circumstances, the monitoring system must be flexible and durable [6, 7].

The three primary data processing methods used in bridge monitoring systems nowadays are distributed data processing, centralized data processing, and edge computing with cloud computing. Among them, centralized data processing techniques mostly depend on a central server for data analysis; however, this approach is less effective at handling large data volumes and is prone to system bottlenecks and data transmission delays [8, 9]. By dividing up the processing work among several sites, distributed data processing techniques boost processing efficiency. However, they also come with high management and maintenance costs and a complex system.

The goal of the new edge-cloud computing solution is to get beyond the drawbacks of the more conventional methods. Cloud computing offers robust storage and deep analytical capabilities, whereas edge computing permits preliminary data processing close to the site of data gathering, reducing the latency of data transmission. This plan can somewhat increase the system's scalability and real-time data processing [10]. However, there are still difficulties in the process of integrating edge computing with cloud computing, including problems with data security, synchronization, and system complexity.

The contribution of this article is as follows:

- The cloud computing system integrates real-time or near real-time monitoring, which enhances the ability to track bridge deformation and response to external factors like wind loads and traffic.
- The system uses preprocessing to clean sensor data and align it with GPS time, followed by post-processing that produces statistical analyses every 10 minutes. This enables detailed tracking of environmental factors and bridge behavior, ensuring timely identification of structural issues.
- The early warning module, which updates baselines and thresholds iteratively, allows for the proactive identification of abnormal structural behavior, thus enhancing safety management.

The remaining sections of this article are structured as follows:

Related work is given in Section II. Section III presents the bridge diagnostic modeling. Section IV discusses the data processing and monitoring module. It explains the bridge structure evaluation and early warning system. It also describes the software development and sensor system. Section V provides the preliminary analysis of bridge deformation, including statistical evaluations from 2021 and 2022. It covers the initial examination of InSAR image data to monitor ground subsidence. Section VI concludes with the overall findings and implications for future work.

II. Related Work

Several researchers have explored SHM systems for bridges, focusing on real-time data collection, processing, and predictive analysis.

Early SHM systems have primarily relied on wired sensor networks and manual data collection, often requiring substantial human intervention for data processing and analysis. These systems also faced limitations in scalability, real-time monitoring, and the ability to handle large volumes of data. More recent studies have introduced cloud computing platforms for SHM systems, enhancing data storage, processing capabilities, and remote access to monitoring data [3, 9]. For instance, Xie et al. [11] mentions the use of GNSS and acceleration data for bridge vibration analysis, similar to the proposed approach. However, these systems often lack advanced real-time fault tolerance mechanisms and high computational efficiency when dealing with large sensor networks. Bayik has also applied InSAR image processing to detect settlement movements around large-scale infrastructure [12]. However, most studies have treated InSAR data as separate from the real-time SHM system, lacking integration into a unified monitoring platform. This limits their utility for ongoing structural assessment and real-time decision-making.

Existing systems often fail to maintain data integrity during network interruptions or connectivity failures, which can cause significant gaps in data during critical periods. While many studies use basic statistical methods for monitoring, there is limited use of intelligent algorithms that integrate GNSS, acceleration, and environmental data for real-time predictive analysis [13].

The research presented in this paper builds on the work of [14] and others by proposing a **comprehensive cloud-based SHM system** that integrates real-time data processing, intelligent predictive analysis, and fault tolerance mechanisms. Through a backup server capable of storing raw sensor data for up to one month, a feature that existing systems lack.

III. Bridge Diagnostic Modeling

The design of the model and the development of formulas are important components in the dynamic monitoring of bridge structures. A realistic and scientific model should be developed for assessing and forecasting the dynamic response of the bridge in order to achieve an accurate diagnosis of the bridge structure. Based on the integrated edge-cloud computing architecture, a bridge diagnostic model design was developed in this study [15, 16].

A finite element model (FEM), which considers the bridge's geometry, material properties, and boundary conditions, can be used to represent the dynamic response of a bridge structure. The dynamic response of the bridge was simulated using a linear elastic FEM.

The following equation of motion can be used to characterize a bridge's dynamic response:

$$M\ddot{u}(t)+C\dot{u}(t)+Ku(t)=F(t) \tag{1}$$

where, M is the quality matrix, representing the quality distribution of the bridge; C is the damping matrix, representing the damping characteristics of the bridge; K is the stiffness matrix, representing the stiffness characteristics of the bridge; $u(t)$ is a displacement vector, representing the dynamic response of the bridge; and $F(t)$ is an external load vector, representing wind load, traffic load, etc.

Modal analysis was applied to the bridge in order to examine its inherent frequencies and vibration modes. The characteristic equation of the modal analysis is as follows:

$$\left(K-\omega^2 M\right)\phi=0 \tag{2}$$

where, ω is the modal frequency, and ϕ is the modal shape. The bridge's inherent frequency and vibration mode can be determined by resolving the characteristic equation.

A. Evaluation of Structural Health

The structural health of bridges was assessed using the features extracted. The bridge's health index HI can be determined using the following formula:

$$HI=\frac{\bar{d}}{\sigma_b} \tag{3}$$

The presence of structural irregularities in the bridge can be established by comparing the health index of HI with a certain threshold. A warning will be sent out if HI surpasses the cutoff.

B. Wind Speed and Deformation Relationship

The following nonlinear regression model can be used to investigate how wind load affects bridge deformation:

$$\delta_{\text{lateral}}=\alpha\cdot V_{\text{wind}}^2+\beta\cdot V_{\text{wind}}+\gamma \tag{4}$$

where, δ_{lateral} is the amount of lateral deformation; V_{wind} is the wind speed; α, β, and γ are the regression coefficients yielded by the regression analysis.

IV. System Architecture for Cloud Computing

Fig. 1 depicts the general architecture of the Federal Reserve System (FRB) cloud computing system, which is broken down into five subsystems: the data management module, the data processing and monitoring module, the data collection and transmission module, the bridge structure evaluation and early warning module, and the sensor module. The components and interactions between the subsystems are depicted in Fig. 2.

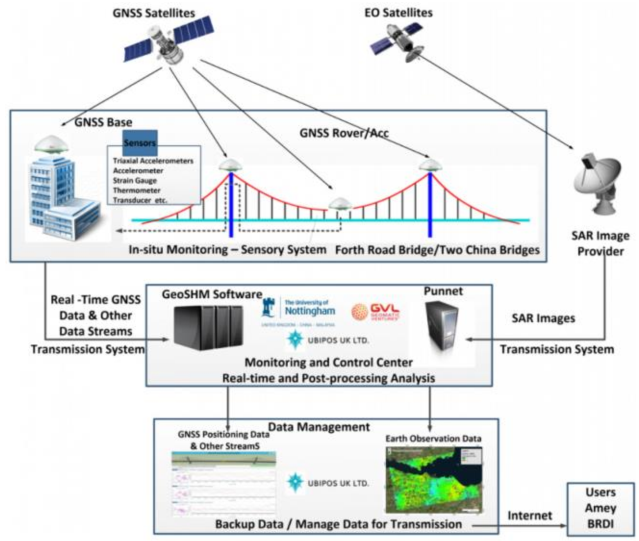

Fig. 1. The overall architecture of the cloud computing system.

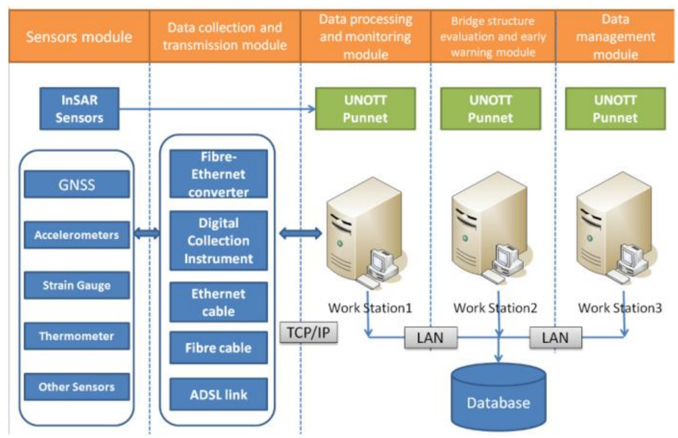

Fig. 2. Data flow and the relationships between the cloud computing subsystems.

C. Sensor Module

The cloud computing's sensor module is made up of various sensor types that can monitor the bridge's displacement, acceleration, inclination, stress, and other structural responses. It can also identify external loads applied to the bridge, such as wind loads and traffic weight, and short- and long-term environmental effects, such as temperature, weather, and ground motion [17, 18]. Fig. 3 illustrates the precise locations of the sensors on the FRB, and Table I lists the different kinds of sensors used in this cloud demonstration project, along with their sampling rates.

Global Navigation Satellite System (GNSS) technology, which makes use of both expensive and low-cost GNSS receivers, forms the basis of the sensor module. A fundamental prerequisite for the creation of an economical sensor module system is the provision of both static profiles and dynamic behavior for both low-cost and high-performance receivers. Three pairs of GNSS receivers were placed across the center and two navigation points in the major region of *B*, in addition to three inexpensive three-axis Sherborne accelerometers. This combination facilitates the integration of acceleration data and

GNSS data for extremely precise measurements of bridge deformation. An accelerometer was also positioned at 1/8 and 3/8 of the major spans, offering more information that could be used to determine the modulation frequency and vibration mode geometries of the FRBs. A triaxial accelerometer was installed atop each of the two major towers since deformation monitoring is critical to their operation. Inclineometers were also erected to show the average deformation at the summits of the towers. In-depth correlation studies of the wind loads on the FRB were made possible by the installation of three anemometers on the structure: two at the top of the two main towers and one at the mid-span. Advanced photovoltaic technology was also used in the cloud computer demonstration project to deliver data on sensors that can negatively impact the main tower foundations and the bridge's overall integrity.

TABLE I. SPECIFICATIONS OF THE SENSORS SET UP FOR THE GEOHAZARD MONITORING REMOTE INITIATIVE

Sensors	Details	Sampling Rates (hz)
GNSS	Leica gro	12
GNSS	Panda DB38	2
Anemometer	Gill windmaster	22
Weather station	Gill Metpak	2
Accelerometer	Sherborne A545-0003-2G	100
Inclinometer	Sherborne LSOP-1	12
InSAR image	EO 1	Image/14 days

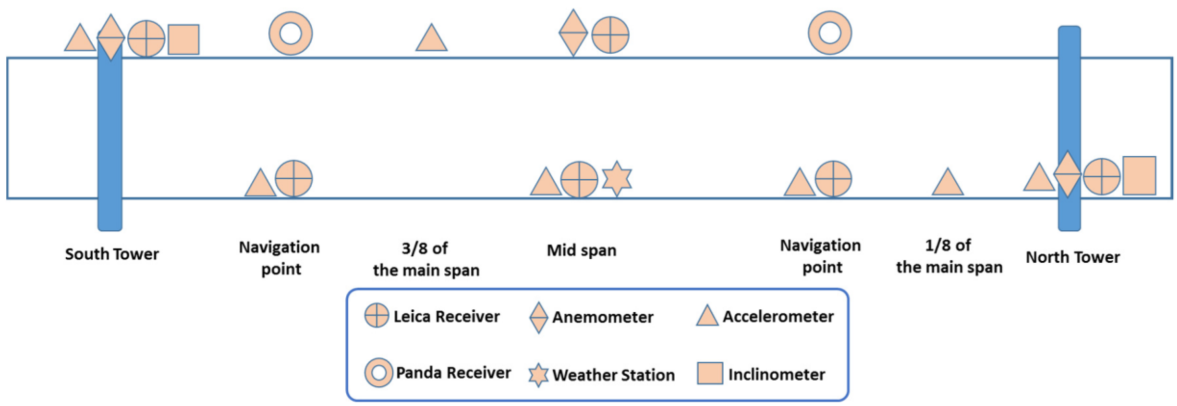

Fig. 3. Installation positions of sensors.

D. Data Collection and Transmission Module

The architecture of the data collection and transmission module installed at the FRB is shown in Fig. 4. The module's primary function is to convey data to a server safely housed in the field control centre using a fiber-optic link for communication with the sensors. Bridge operators can use this server to download data for additional analysis, generate reports on a regular basis, and access monitoring data for real-time monitoring. More crucially, in the event that communication between the bridge site and the main cloud server is lost, this server serves as a backup server, temporarily storing raw sensor data. The backup server is built to hold roughly one month's worth of raw sensor data, which is adequate in the case of a potential connectivity failure given the high sampling rate and numerous sensors.

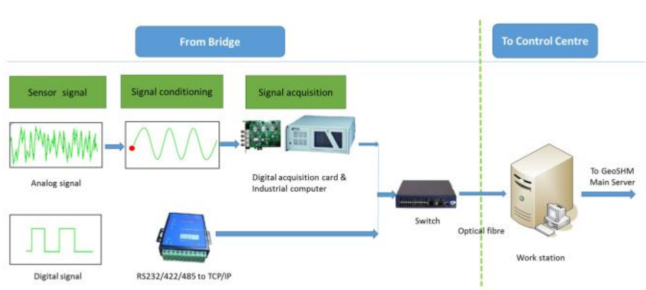

Fig. 4. Schematic diagram of the data collection and transmission module for cloud computing.

E. Data Processing and Monitoring Module

Preprocessing and post-processing units make up the two components of the data processing and monitoring module, which is primarily installed on the primary cloud computing server (Fig. 5). The primary duties of the preprocessing unit are to detect and eliminate anomalies and synchronize all sensor data with GPS time. The preprocessing unit also transforms the bridge deformation data in the bridge coordinate system from the purified GNSS data. The post-processing unit receives the output from the preprocessing unit [19].

The post-processing unit statistically assesses features pertaining to environmental impacts, external loads, and bridge deformation to produce statistical averages that are updated every 10 minutes. These characteristics include the average air temperature, the peak wind coefficient, the average inclination of the main tower, and the mean and standard deviation of the bridge deformation in the span. The cloud computing data strategy provides a precise definition for these low-level aspects.

The cloud computing system has an automatic and advanced system identification algorithm that uses GNSS and acceleration data to predict the modal frequencies and shapes of vibration patterns in order to perform intelligent data analysis. Furthermore, the device possesses real-time or almost real-time monitoring capabilities that leverage the previously mentioned attributes to track bridge deformation in response to wind loads and additional operational and environmental variables [20, 21].

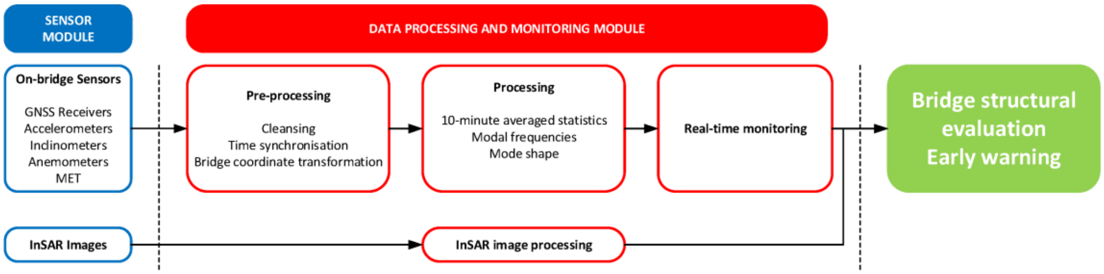

Fig. 5. Main features of the data processing and monitoring module for cloud computing.

It is noteworthy that, because of its low cost and high computational needs, Interferometric Synthetic Aperture Radar (InSAR) image processing is carried out on a monthly basis. This makes sense because, in contrast, settlement takes place over a longer time frame.

F. Bridge Structure Evaluation and Early Warning Module

The design and execution of an alert system based on the requirements of the cloud computing data policy are shown in Fig. 6. This module's performance depends on baselines and thresholds that were initially established using previous monitoring data and bridge operator expertise. These baselines and thresholds were then continuously refined using an iterative update mechanism to accurately reflect the bridge's current condition. When the measured bridge reaction goes over these limits and baselines, an alarm will sound, signaling that the bridge's structural behavior is aberrant.

A more sophisticated structural evaluation process can be utilized to investigate an alarm further after it has been set off. This helps identify whether the alarm is caused by alterations in the operating and environmental circumstances, modifications to the structural system, or the failure of a member. Additionally, the method uses modal parameters taken out of the deformation data to update the structural model in a rolling fashion. By facilitating simulation, the updated model helps bridge operators make better management decisions [22].

When the findings of InSAR image processing are obtained, they are applied to a structural model in order to evaluate how long-term ground motion affects structural stiffness. Bridge stability and long-term safety can be improved with the use of this procedure.

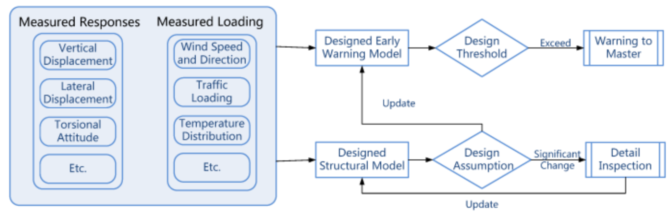

Fig. 6. Module flowchart for cloud computing.

V. Experimentation

A. Software Development and Sensor System Status

A cloud computing web application was developed in terms of software, as seen in Fig. 7. User engagement with the cloud computing system is facilitated by the platform. Some of this web application's functions are available to users, such as real-time monitoring, immediate alarms, and historical data queries. The following section goes into additional detail about a few of the outcomes this web application produces.

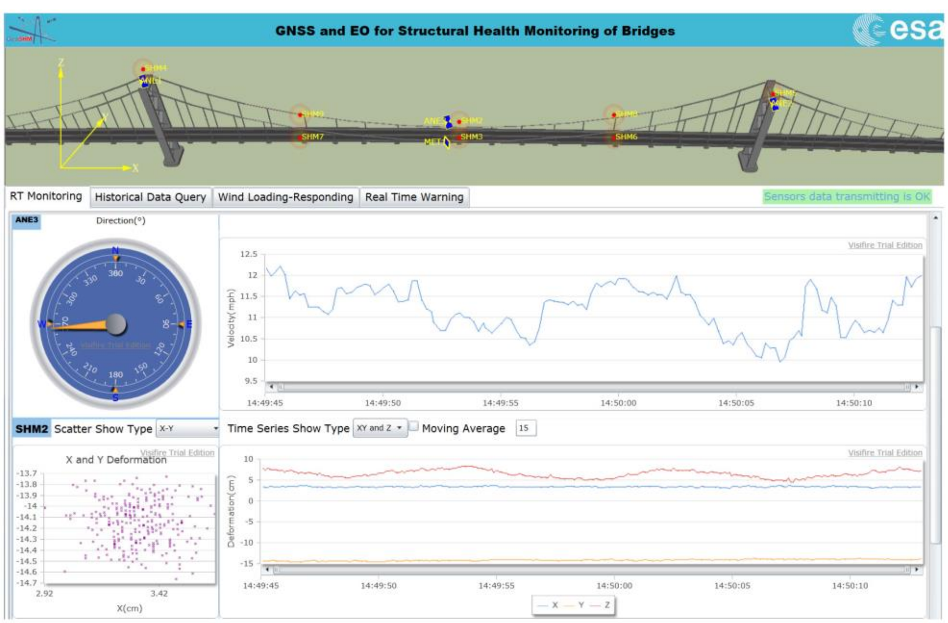

Fig. 7. Web applications for cloud computing.

B. Preliminary Analysis of Bridge Deformation

The cloud computing web application gives customers access to 10-minute average feature statistics from the cloud computing database in addition to real-time monitoring. With the help of this capability, the user may comprehend the bridge's response patterns and history as well as further examine how the bridge reacts to system changes or structural part failures. Furthermore, the 10-minute average statistics for temperature, wind speed, intrinsic frequency, and bridge response evaluation are crucial for establishing baselines, thresholds, and short- and long-term trends. These data are important for developing bridge structure evaluation and warning algorithms, as well as for evaluating the typical structural behavior of FRBs under various operational and environmental situations. This section presents and discusses a few of the evaluations' findings.

The cloud computing web application has the ability to automatically create several kinds of statistical graphs on demand. MATLAB was utilized for their high-resolution presentations. The main focus is on the 10-minute mean and standard deviation responses of the FRBs, along with their relationship to wind speed, air temperature, and traffic. The bridge's response involves deformation in four directions: vertical (along the *z*-axis), torsional (around the *x*-axis), transverse (along the *y*-axis), and longitudinal (along the *x*-axis). The bridge's steady state is represented by the 10-minute mean of its long-term deformation, and its dynamic reaction is shown by the 10-minute standard deviation.

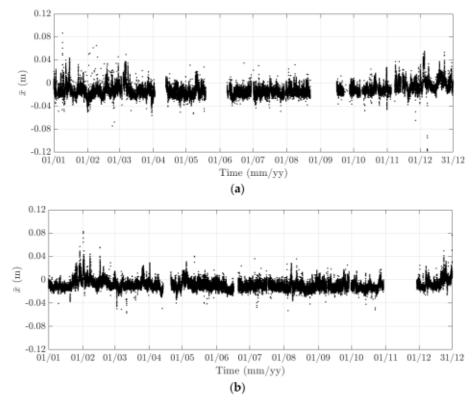

Fig. 8. The 10-minute mean changes in the longitudinal response in (a) 2021 and (b) 2022 throughout the FRB.

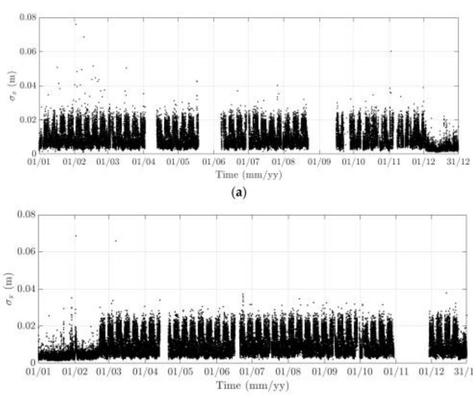

Fig. 9. The 10-minute standard deviation changes in longitudinal response across the FRB in (a) 2021 and (b) 2022.

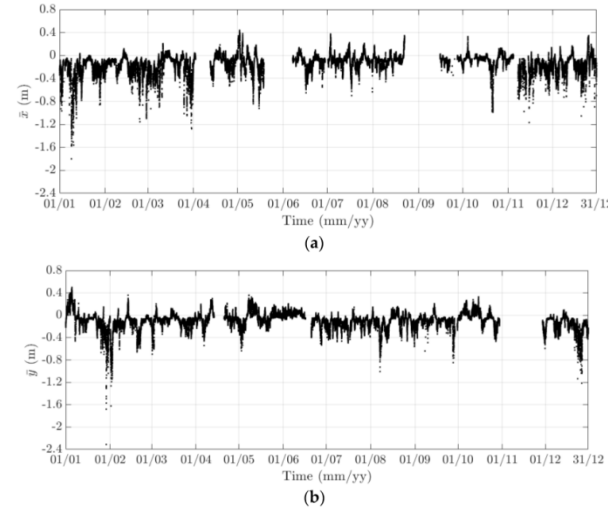

Fig. 10. The 10-minute mean changes in the lateral response across the FRB in (a) 2021 and (b) 2022.

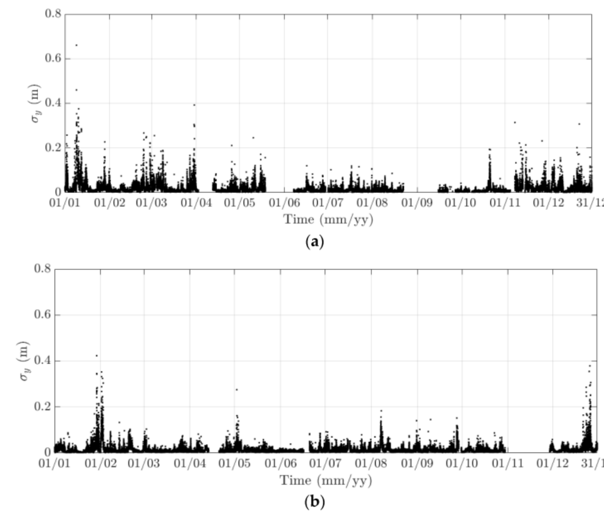

Fig. 11. Variation of lateral response in FRB in span (10-minute standard deviation) for years 2021 and 2022.

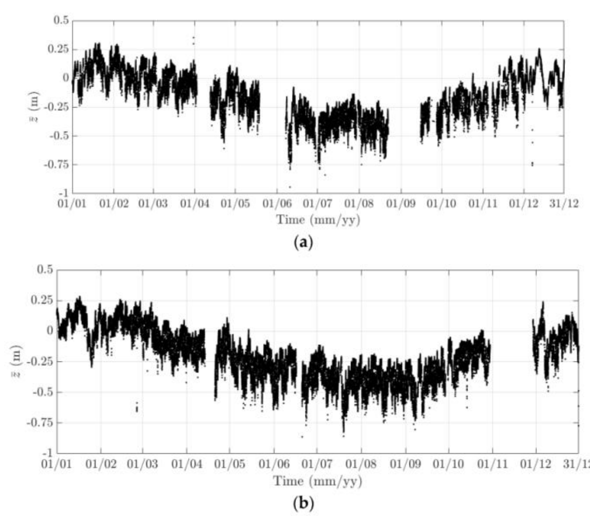

Fig. 12. The average 10-minute heave response changed in 2021 and 2022 throughout the FRB.

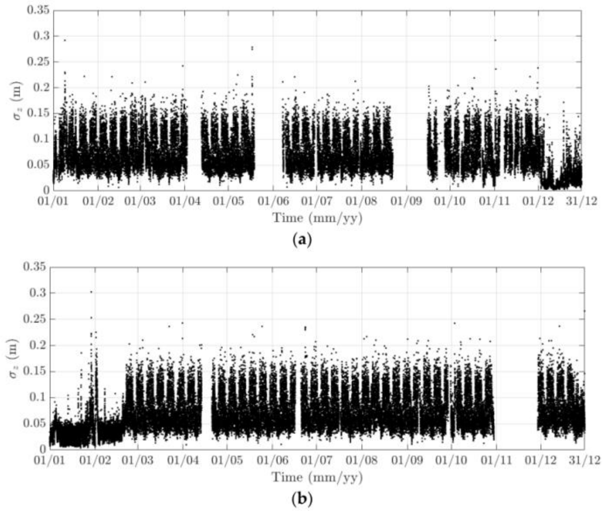

Fig. 13. Variations in the 10-minute standard deviation of the FRB oscillating respiration in (a) 2021 and (b) 2022.

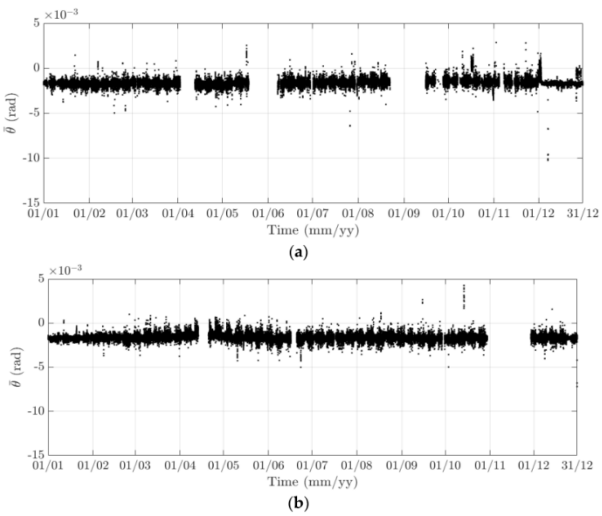

Fig. 14. Torsional response changes throughout a 10-minute period in the FRB in (a) 2021 and (b) 2022.

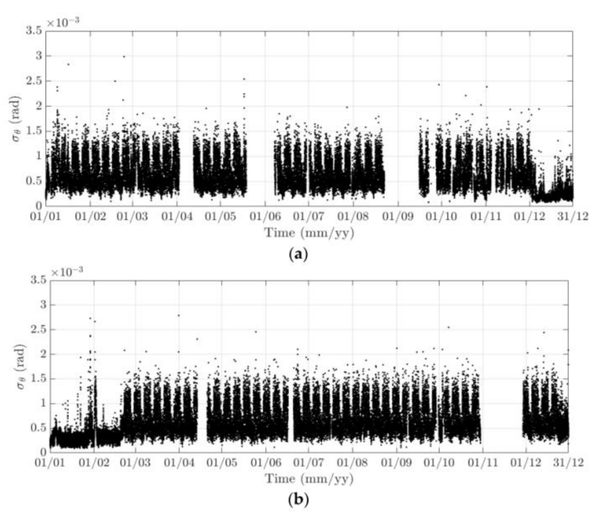

Fig. 15. Torsional response over the FRB in (a) 2021 and (b) 2022: 10-minute standard deviation change.

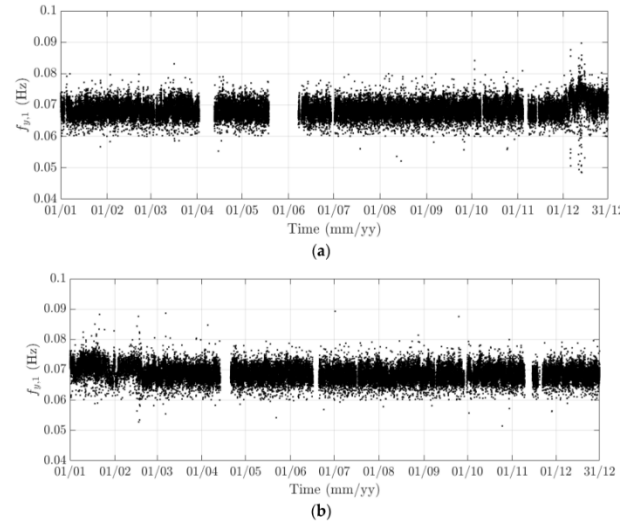

Fig. 16. Intrinsic frequency variations during a 10-minute period for the initial transverse model in (a) 2021 and (b) 2022.

Periodic characteristics of the bridge response and intrinsic frequency were identified through the analysis of the monitoring data for the years 2021 and 2022. These characteristics can be categorized into daily and weekly cycles. Certain data collected by the SHM system on the 560-meter Chinese bridge in Hong Kong, Zhuhai, and Macao bears a striking resemblance to some of these observations [23]. As further discussed in this section, the bridge response and the intrinsic frequency, however, frequently do not follow these patterns. Fig. 8 to Fig. 9 display the 10-minute averaged features for the years 2021 and 2022. Fig. 10 to Fig. 11 offer a thorough examination of a few chosen features for a brief period of time (August 1 to August 14, 2022).

A pattern of diurnal cycles is evident when examining the 10-minute standard deviations of the longitudinal response (Fig. 12), undulation response (Fig. 13), and torsion response (Fig. 14). These 10-minute average figures for the period August 1-14, 2022, demonstrate notable variations between day and night. The variance in traffic flow is closely related to the fact that the standard deviation values are substantially higher during the day than at night. The dynamic reaction is most intense when traffic peaks between 03:00 and 04:00, and it tapers off after 15:00 when traffic starts to decline.

Weekday traffic volume is higher than weekend traffic volume, which also results in a larger standard deviation fluctuation. Furthermore, the analysis of the 10-minute averages of the undulation deformation (Fig. 14), which represents the amount of sag in the mid-span of the FRB, can provide additional insight into the diurnal periodicity. Fig. 18 demonstrates a distinct sag volume difference between day and night; however, this cyclical pattern is less evident because of natural temperature swings. The lower weekend traffic results in a drop in the sag volume at the midspan. The 10-minute natural frequencies of the initial transverse and undulation patterns (Fig. 15, 16, and 17) also depict these diurnal cycles. These frequencies decreased by 7% and 2%, respectively, as a result of warmer daytime temperatures and more mass brought on by traffic; on weekends, this pattern was less noticeable.

There are multiple instances in 2021 and 2022 with bridge response and intrinsic frequency deviating from the average trend: (i) early January 2021; (ii) December 2021 through February 2022; and (iii) late December 2022. During these periods, the intrinsic frequency rises dramatically, particularly during (ii), but the change in standard deviation within a day is negligible. It was discovered that the primary cause of the temperature and traffic fluctuations during these occurrences was the decreased volume of traffic on the bridges. To be more precise, (i) and (iii) are both public holidays (such as Christmas and New Year's), whereas (ii) is connected to the break in the northeast end-connection, which led to traffic restrictions and bridge closures. The 10-min averages of torsional and longitudinal responses were significantly altered by these events, but the 10-min averages of sag deformation were only slightly affected (Fig. 8 and Fig. 14).

Furthermore, an obvious annual cycle can be seen in the 10-minute average heave deformation (Fig. 14). The temperature increase caused the sag in the middle of the FRB span to progressively climb from January through August, eventually reaching a mean value of about 0.4 m. After August, as the outside temperature dropped, the FRB progressively moved back to its former location. There was no discernible annual cycle in the other bridge response or intrinsic frequency components. The data showed more random behavior with no discernible short- or long-term trends, as evidenced by the 10-minute averages and standard deviations of lateral deformations that were mostly impacted by wind speed (Fig. 12 and Fig. 13). On the other hand, as shown in Fig. 12, the analysis of the wind load response demonstrates a quadratic relationship between the mean lateral deformation and the positive component of the mean wind speed. The lower and upper thresholds, denoted as Un, are shown in Fig. 17, where circle is the standard deviation of the data samples for the positive component of mean wind speed within a window of three seconds. Though some data points considerably depart from the specified quadratic curve or exceed the upper threshold, most data points fall between these two criteria.

Upon examining the monitoring data from 2021 and 2022, certain distinctive characteristics of the FRB's structural response under external excitation were discovered. Certain recurrent patterns of bridge response and modal frequencies were affected by temperature. Based on their cause and duration, these patterns were divided into daily, weekly, and annual cycles. Certain departures from these cyclic patterns were found to be triggered by changes in operational conditions brought on by public holidays or FRB closures. Furthermore, in order to guarantee a normal structural reaction of the FRB in the event of severe wind, lower and upper bounds on the wind-induced response were established. It is critical to establish these characteristic behaviors of the FRB for subsequent years of monitoring data analysis, thereby helping identify systematic changes in the structure and their causes, which is an important part of the development of the cloud data strategy.

C. Initial Examination of InSAR Pictures

In this part, some initial findings from the InSAR image processing encompassing the Sanqi Bridge (Shanghai, China) and the surrounding area of the FRB are presented. As depicted in Fig. 18, the movement of subsidence in the vicinity of the FRB is minimal, mostly within a radius of approximately 2 km from the FRB, where its influence is minimal. In certain regions, the movement is at a rate of around 5 mm/year. On the other hand, Fig. 19 for the Sanqi Bridge (Shanghai, China) demonstrates that there are notable settlement movements occurring in the vicinity of the bridge, up to a maximum of 20 mm annually, in the area 1 km away. These settlement patterns move in the direction of the bridge, endangering its structural stability.

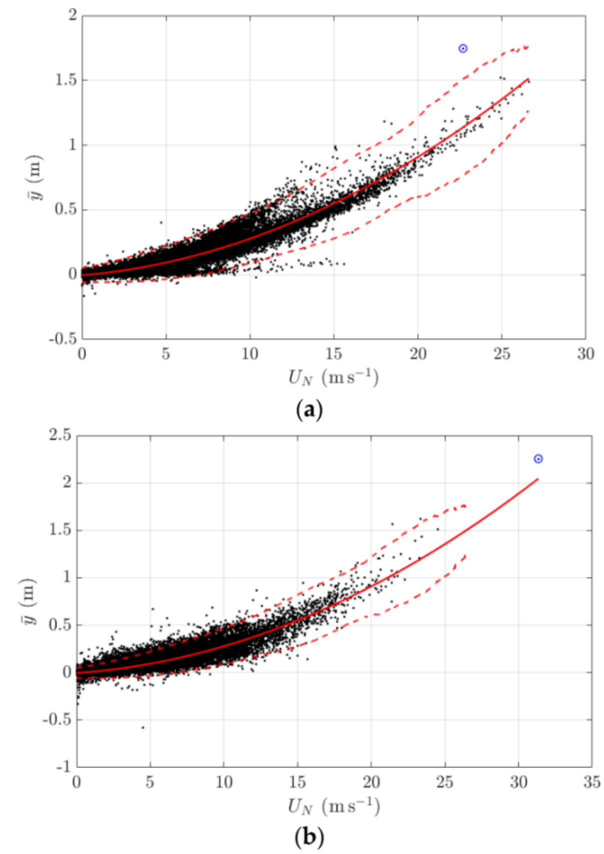

Fig. 17. Comparison of the produced quadratic curves and thresholds in (a) 2021 and (b) 2022, with blue circles representing extreme events.

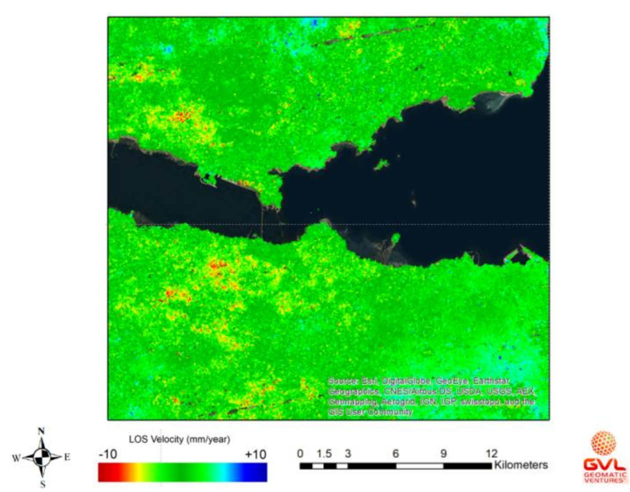

Fig. 18. InSAR image processing of the Sanqi Bridge (October 2017).

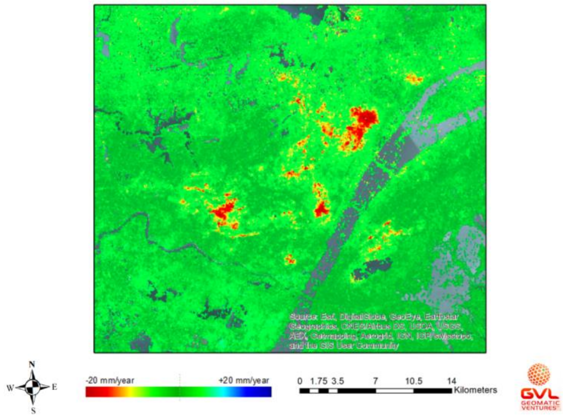

Fig. 19. InSAR image processing of the surrounding area of the Sanqi Bridge (December 2023).

VI. Conclusion

This paper presents a cloud-based SHM system for long-span bridges, integrating GNSS, accelerometers, and InSAR technologies for real-time data collection and analysis. The system ensures continuous monitoring through a fiber-optic communication link and a backup server, while the cloud processing module refines data accuracy and evaluates structural responses to environmental factors. We observed cyclical patterns in bridge behavior influenced by traffic and temperature, and detected anomalies linked to specific events. While the system shows promise in providing real-time insights, limitations include the infrequent processing of InSAR data and challenges in scaling to larger infrastructures. Future work will address these challenges and further optimize the system for broader applications in infrastructure monitoring.

Building on our paper, future work could focus on several key areas to enhance and expand the capabilities of the proposed SHM system: Address the infrequent processing of InSAR images by developing more efficient algorithms or increasing processing frequency. This will provide more timely insights into long-term ground movement and its impact on structural health. Explore the incorporation of other sensor types, such as acoustic emission sensors or fiber optic sensors, to capture a broader range of structural responses and potential failure mechanisms. Improve the data processing and analysis algorithms to better handle large volumes of data and detect subtle anomalies. This could involve advanced machine learning techniques or AI-based predictive models.

References

[1] Al-Ali AR, Beheiry S, Alnabulsi A, Obaid S, Mansoor N, Odeh N, Mostafa A. An IoT-based road bridge health monitoring and warning system. Sensors, 2024;24(2):469.

[2] Wang T, Liang Y, Shen X, Zheng X, Mahmood A, Sheng QZ. Edge computing and sensor-cloud: Overview, solutions, and directions. ACM Computing Surveys, 2023, 55(13s):1-37.

[3] Peng Z, Li J, Hao H. Development and experimental verification of an IoT sensing system for drive-by bridge health monitoring. Engineering Structures, 2023;293:116705.

[4] Yuan J, Xiao H, Shen Z, Zhang T, Jin J. ELECT: Energy-efficient intelligent edge–cloud collaboration for remote IoT services. Future Generation Computer Systems, 2023;147:179-194.

[5] Kyriou A, Mpelogianni V, Nikolakopoulos K, Groumpos PP. Review of Remote Sensing Approaches and Soft Computing for Infrastructure Monitoring. Geomatics, 2023;3(3):367-392.

[6] Tan Y, Yi W, Chen P, Zou Y. An adaptive crack inspection method for building surface based on BIM, UAV and edge computing. Automation in Construction, 2024;157:105161.

[7] Su W, Xu G, He Z, Machica IK., Quimno V, Du Y, Kong Y. Cloud-edge computing-based ICICOS framework for industrial automation and artificial intelligence: a survey. Journal of Circuits, Systems and Computers, 2023:32(10):2350168.

[8] Chen Q, Cao J, Zhu S. Data-driven monitoring and predictive maintenance for engineering structures: Technologies, implementation challenges, and future directions. IEEE Internet of Things Journal, 2023;10(16):14527-14551.

[9] Liang W, Xiao J, Chen Y, Yang C, Xie K, Li KC, Di Martino B. TMHD: Twin-bridge scheduling of multi-heterogeneous dependent tasks for edge computing. Future Generation Computer Systems, 2024;158:60-72.

[10] Costin A, Adibfar A, Bridge J. Digital twin framework for bridge structural health monitoring utilizing existing technologies: New paradigm for enhanced management, operation, and maintenance. Transportation Research Record, 2024;2678(6):1095-1106.

[11] Xie Y, Zhang S, Meng X, Nguyen DT, Ye G, Li H. An innovative sensor integrated with GNSS and accelerometer for bridge health monitoring. Remote Sens. 2024;16:607. https://doi.org/10.3390/rs16040607

[12] Bayik C, Abdikan S, Ozdemir A, Arıkan M, Sanli FB, Dogan U. Investigation of the landslides in Beylikdüzü-Esenyurt Districts of Istanbul from InSAR and GNSS observations. Nat Hazards. 2021;109:1201–1220. https://doi.org/10.1007/s11069-021-04875-7

[13] Zhuang C, Zhao H, Hu S, Sun C, Feng W. Integrity Monitoring Algorithm for GNSS-based Cooperative Positioning Applications. Proceedings of the 32nd International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2019). Miami, Florida, September 2019; pp. 2008-2022. https://doi.org/10.33012/2019.16881

[14] Mishra M, Lourenço PB, Ramana GV. Structural health monitoring of civil engineering structures by using the internet of things: A review. J Build Eng. 2022;48:103954. https://doi.org/10.1016/j.jobe.2021.103954

[15] Zhang C, Zhou G, Li J, Chang F, Ding K, Ma D. A multi-access edge computing enabled framework for the construction of a knowledge-sharing intelligent machine tool swarm in Industry 4.0. Journal of Manufacturing Systems, 2023;66:56-70.

[16] Raeisi-Varzaneh M, Dakkak O, Habbal A, Kim BS. Resource scheduling in edge computing: Architecture, taxonomy, open issues and future research directions. IEEE Access, 2023, 11: 25329-25350.

[17] Negi P, Singh R, Gehlot A, Kathuria S, Thakur AK, Gupta LR, Abbas M. Specific soft computing strategies for the digitalization of infrastructure and its sustainability: A comprehensive analysis. Archives of Computational Methods in Engineering, 2024;31(3):1341-1362.

[18] Sadhu A, Peplinski JE, Mohammadkhorasani A, Moreu F. A review of data management and visualization techniques for structural health monitoring using BIM and virtual or augmented reality. Journal of Structural Engineering, 2023;149(1):03122006.

[19] Kumar R, Sangwan KS, Herrmann C, Thakur S. A cyber physical production system framework for online monitoring, visualization and control by using cloud, fog, and edge computing technologies. International Journal of Computer Integrated Manufacturing, 2023;36(10):1507-1525.

[20] Guo Z, Yu K, Kumar N, Wei W, Mumtaz S, Guizani M. Deep-distributed-learning-based POI recommendation under mobile-edge networks. IEEE Internet of Things Journal, 2022;10(1):303-317.

[21] Zhang C, Roh BH, Shan G. (2023). Poster: Dynamic clustered federated framework for multi-domain network anomaly detection. In Companion of the 19th International Conference on emerging Networking EXperiments and Technologies NY, USA, 2023;pp.71-72.

[22] Gong T, Zhu L, Yu FR, Tang T. Edge intelligence in intelligent transportation systems: A survey. IEEE Transactions on Intelligent Transportation Systems, 2023;24(9):8919-8944.

[23] Dai Z, Zhang Q, Zhao L, Zhu X, Zhou D. Cloud-Edge computing technology-based internet of things system for smart classroom environment. International Journal of Emerging Technologies in Learning, 2023;18(8):79-96.