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# Integrated Sensor Fusion Device with an Optimized Mathematical Model to Monitor Civil Engineering Structures

Jianling TAN*, Dan LI

**Abstract:** Integrated sensor fusion is a new technique in which multiple sensors intelligently combine data to support application or system performance improvement software. With this method, many sensors combine data for accurate position and orientation information to overcome the inadequacy of each sensor. Data consolidation can be described as measuring the state of an entity as a mixture of data or information. This multidisciplinary field has several advantages, including increased confidence, reliability, and reduced ambiguity when measuring company conditions in engineered systems. This paper discusses the various applications of data fusion in civil engineering in recent years, and puts forward some potential advantages of data fusion in civil engineering. Mathematical modeling (MM) is the skill to transform challenges from application to tractable mathematical formulations that provide insight, answers, and instructions in the theoretical and numerical analysis of the original application. This article presented an integer linear programming mathematical model to divide building activities in a project to solve building planning problems. MMCE (Mathematical Modeling Conceptual Evaluation) introduced it to complete an accurate and quick estimation of civil systems such as traffic networks, structural systems, and building projects, becoming more and more achievable through omnipresent sensor networks and communications systems. By assessing the condition of the system, it can make better decisions more rapidly and better. This has enormous value and a variety of impacts. Fusion data is an essential element of system status assessment. Applications and needs for research are underlined for the future.

**Keywords:** civil engineering; data fusion; mathematical model; sensor fusion; structure

## 1 INTRODUCTION

To ensure that civil engineering structures are reliable within prescribed parameters, measurements are gathered and analyzed, allowing condition-based measures to be taken [1]. These measurements can generate information that is either extremely similar, frequently from the identical sensor, or entirely different, depending on the approach used [2, 3]. Traditionally, skilled professionals and experts have analyzed this data [4]. However, as computational power increases and new and unique detecting methods are developed [5], the information gathered must be processed reliably and systematically [6]. As a result, computational algorithms capable of retrieving useful data from historical information have been developed [7]. Data fusion refers to the combination of data collected from numerous sensing systems and intelligence [8, 9].

When similar sensors are utilized in a multi-sensor network, the information processing process may be completed quickly [10]. The heterogeneity of the data can improve the reliability of the outcomes [11]. When multiple sensors are employed [12], the data gathered must be converted into a standard format and time-aligned [13]. Information can be merged as it enters the network or at a predefined level throughout the fusion mechanism [14, 15]. The dependability of the data utilized inside the fusion mechanism will be determined by the sensors accessible and the methods utilized for data fusion [16, 17]. The choice of sensors, as the number of sensors required to improve the reliability of the information conveyed, is determined based on the solution needed [18].

The development of wireless sensor networks for monitoring civil engineering structures is of considerable interest [19, 20]. Corrosion is a significant issue for engineering structures, causing significant degradation [21], rising operational costs [22], and lowering reliability [23]. However, whereas cast iron is one of the primary causes of reactive corrosion in reinforced civil structures [24], it appears to have only a tangential role in influencing the corrosion rate of metallic reinforcement [25]. The corrosion ratio of the reinforcing steel is further influenced by ambient parameters such as acidification of the concrete mix [26], pH of the cement pore water [27], oxygen concentration [28], temperature level [29], and humidity levels [30], and all are interconnected. Corrosion monitoring is thus a critical problem for community security and infrastructure maintenance [31, 32].

With the acceleration of the process of modern urbanization, the construction of civil engineering structures such as high Bridges, tunnels and large buildings is also increasing. Monitoring the performance of these structures by scientific and technological means, understanding the various conditions of the structures as early as possible, and carrying out repairs and maintenance when necessary, can help extend the service life of the structures and improve the safety, reliability and economy of the structures. Therefore, it is of great significance to study the performance monitoring system and damage identification method of civil engineering structures. The present paper explores various recent data fusion applications in civil engineering (CE) and presents some potential advantages of data fusion in civil engineering. Mathematical modeling (MM) is the skill to transform challenges from application to tractable mathematical formulations that provide insight, answers, and instructions in the theoretical and numerical analysis of the original application. This article presented an integer linear programming mathematical model to divide building activities in a project to solve building planning problems. The important research objects of the study are listed as follows.

- The architecture of the integrated sensor fusion model for monitoring civil engineering structures is detailed.
- A conceptual description of an optimization mathematical model for analyzing building conditions is introduced in detail.
- The developed integrated approach for monitoring the civil engineering structures is detailed.

The rest of the study is structured as follows. The second chapter introduces the literary works in detail. In chapter 3, the architecture of integrated sensor fusion model is discussed. In chapter 3, the concept of optimization mathematical model is discussed. In chapter 4, the integration of sensor fusion device and optimization mathematical model is discussed. The experimental results are discussed in chapter 5, and the optimal results are summarized.

## 2 LITERATURE STUDY

Generally, mathematical modeling is employed for the design of the experiment (DOE) [33]. During the design of civil engineering structures, the basis of the design of the experiment and statistical analysis comprises mathematical correlations between input and output variables such as raw material attributes and utilization and technical variables [34, 35]. This enables comprehensive monitoring and refinement of the technological process with lower capital costs and the creation of highly efficient building structures with the needed functionality [36, 37]. Various non-destructive methods have been developed to monitor the civil engineering structures most reliably [38], and some of the methods are described as follows.

Zhang et al. [39] introduced the capacitive imaging approach (CIA), which identifies changes in the local electrical properties of civil engineering structures using a coupler capacitive probe linked to a monitoring network. A fixed frequency alternating current signal is delivered as the controlling voltage to one electrode terminal during the assessment at any given point. However, it is critical to adjust the electrode configuration for each location. A larger electrode assembly provides a higher penetration depth into the sample, but a spatial resolution at the surface offsets this.

Zhu [40] processed the eddy current pattern (ECP) and correlated it to a transfer function to remove the effects of changes in raw material characteristics. Conductivity, flaws, and dimensional variations in the steel reinforcement caused the resultant signal variation. The frequency of excitation determines the penetration depth. This technique can identify extreme forms of corrosion in civil engineering structures but does not offer data on corrosion commencement.

Wu and Jahanshahi [41] proposed the multi-sensor network (MSN) to monitor civil engineering structures. When multiple sensors are employed, the data gathered must be converted into a standard format and time-aligned. Information can be merged as it enters the network or at a predefined level throughout the fusion mechanism. The dependability of the data utilized inside the fusion mechanism will be determined by the sensors accessible and the methods utilized for data fusion.

Das and Saha [42] designed and developed a wireless sensor fusion (WSF) system to monitor civil engineering structure failure-related characteristics such as linear electrical resistivity, permeability, and chloride proportion. These metrics measure characteristics at the surface of the reinforcing steel and forecast the civil structure condition. Measuring these characteristics provides important data, but the sensors are costly and not readily available.

It is critical to discover civil and structural failures early on to intervene effectively and reduce the consequences of such failures [43]. In the study of civil engineering structural performance monitoring system, in addition to the above mentioned content, it is also necessary to develop and apply optimization algorithms and models, and establish a complete data management and maintenance system. In addition, with the continuous development of artificial intelligence, big data and other technologies, these high and new technologies can also be used to improve the accuracy and efficiency of the Shimu engineering structural performance monitoring system, so as to better ensure the safety and stability of civil engineering structures. Based on the literature study, this article presented an integer linear programming mathematical model to divide building activities in a project to solve building planning problems. MMCE (Mathematical Modeling Conceptual Evaluation) introduced it to complete an accurate and quick estimation of civil systems such as traffic networks, structural systems, and building projects, becoming more and more achievable through omnipresent sensor networks and communications systems.

## 3 INTEGRATED SENSOR FUSION MODEL

Integrated sensor fusion is a new technique in which multiple sensors intelligently combine data to support application or system performance improvement software. With this method, many sensors combine data for accurate position and orientation information to overcome the inadequacy of each sensor. The merge of data may be characterized to measure an entity's status as a mixture of data or information. A generic data fusion network based on an integrated multi-sensor platform is illustrated in Fig. 1.

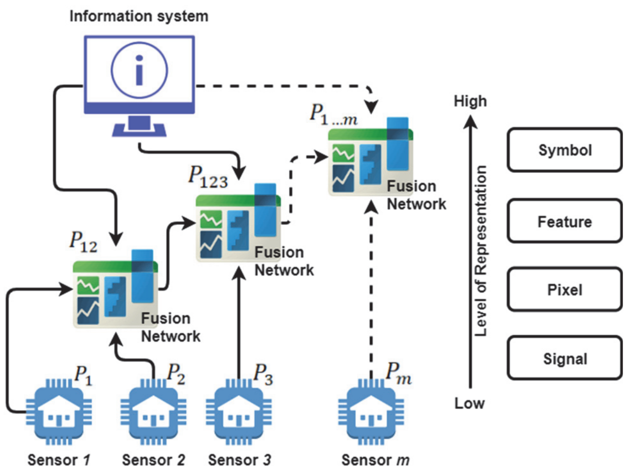


**Figure 1** Integrated multi-sensor platform

This approach integrated data from multiple sources into a hierarchical fashion and embedded it in integrated sensor fusion centers. They drew a clear difference between multi-sensor incorporation and integrated sensor fusion. Multi-sensor incorporation involves utilizing numerous sensor data to help in a specific job. In contrast, integrated sensor fusion refers to any step in the integration phase when data is combined.

Fig. 1 indicates the structure to indicate the multi-sensor incorporation and integrated sensor fusion concurrently. The data gathered at the sensor level is transmitted hierarchically and sequentially to the sensor fusion centers, where the fusion mechanism occurs. After processing the outputs of the *m* sensors, with the assistance of the computer system, if needed, a description of the detected phenomena is generated. Information management, which includes appropriate resources and archives, facilitates the sensor fusion process. As information is merged at the many fusion centers, the degree of abstraction required rises from original information or signal interpretations to more abstracted symbolic interpretations of the information at the symbol stage.

When similar sensors are utilized in a multi-sensor network, the information processing process may be completed quickly. The heterogeneity of the data can improve the reliability of the outcomes. When multiple sensors are employed, the data gathered must be converted into a standard format and time-aligned. Information can be merged as it enters the network or at a predefined level throughout the fusion mechanism. The dependability of the data utilized inside the fusion mechanism will be determined by the sensors accessible and the methods utilized for data fusion.

### 3.1 Optimized Mathematical Model

This paper develops the mathematical model using the regression equation technique. It is developed based on DOE, including various input parameters and task elements. All input variables ($P_1, P_2, P_3, \ldots, P_m$) vary at the following matrices: basic metric (0), low metric (−1), high metric (1) with variability index ($\Delta P_j$) between the matrices [44, 45]. Based on DOE, the conditions of the civil engineering structure are prepared. Analysis of experimental outcomes is executed utilizing mathematical models. As an outcome, the polynomial model is developed and illustrates the interaction between the input and output variables. The regression model $q$ for the two factorial designs of the experiment is expressed in Eq. (1).

$$q = c_0 + c_1 p_1 + c_2 p_2 + c_3 p_1^2 + c_4 p_2^2 + c_5 p_1 p_2 \tag{1}$$

whereas $c_1$, $c_2$, $c_3$, $c_4$, $c_5$ are the coefficients of the developed regression model, and their calculations are expressed in Eqs. (2), (3), (4), and (5).

$$c_0 = U_1 \sum_1^M q_x - U_2 \sum_1^L \left[ \sum_1^M p_{jx}^2 q_x \right] \tag{2}$$

$$c_j = U_3 \sum_1^M p_{jx} q_x \tag{3}$$

$$c_{jj} = U_4 \sum_1^M p_{jx}^2 q_x + U_5 \sum_1^L \left[ \sum_1^M p_{jx}^2 q_x \right] - U_2 \sum_1^M q_x \tag{4}$$

$$c_{jk} = U_6 \sum_1^M p_{jx} p_{kx} q_x \tag{5}$$

whereas $U_1$, $U_2$, …, $U_6$ represents the sensor data, $q_x$ represents the experimental value of the response variable, $x$ represents the point index, $p_j$ represents the index form of $j$-variable. The term $M$ represents the index number in the regression matrix, and $L$ represents the number of variables in the regression matrix. Based on the experimental flow, the statistical confirmation of the coefficient significance and probability evaluation of the developed regression model to describe an interaction between the observed variables are accomplished [46]. The probability evaluation and effectiveness of the developed regression model are generally obtained by analysis of the following metrics.

The statistical mean value for the response factor $\overline{q_x}$ is calculated using row-wise matrix replication and expressed in Eq. (6).

$$\overline{q_x} = \frac{q_{x1} + q_{x2} + \ldots + q_{xs}}{s} \tag{6}$$

whereas $s$ represents the quantity of row-wise matrix replication, and the index of the response variable is identified for the statistical experiment in zero nodes.

The mean square error for the response variable is calculated using row-wise matrix replication and expressed in Eq. (7).

$$E_{qx}^2 = \frac{\sum_1^M \sum_1^s \left( q_{xj} - \overline{q_x} \right)^2}{M(s-1)} \tag{7}$$

whereas $\sum_1^s$, represents the sum of row matrix and $\sum_1^M$, represents the sum of the column matrix.

The mean square tolerance for the response variable is interconnected with the experimental deviation and calculated using experiment matrix replication and expressed in Eq. (8).

$$E_{qx} = \sqrt{E_{qx}^2} \tag{8}$$

The mean square error for the coefficients of the developed regression model is calculated using row-wise matrix replication and expressed in Eq. (9).

$$E_{c_0} = U_7 E_{qx}; E_{c_j} = U_8 E_{qx}; E_{c_{jj}} = U_9 E_{qx}; E_{c_{jk}} = U_{10} E_{qx} \tag{9}$$

whereas $U_7$, $U_8$, …, $U_{10}$ represents the sensor data, $E_{qx}$ represents the mean square tolerance.

The criterion index $I_c$ for each coefficient of the developed regression model is calculated and expressed in Eq. (10).

$$I_{c(c_0)} = \frac{|c_0|}{E_{c_0}}; I_{c(c_j)} = \frac{|c_j|}{E_{c_j}}; I_{c(c_{jj})} = \frac{|c_{jj}|}{E_{c_{jj}}}; I_{c(c_{jk})} = \frac{|c_{jk}|}{E_{c_{jk}}} \tag{10}$$

The calculated coefficients of the developed regression model are pertinent if the criterion index $I_c > U_m$ considering an essential index of connotation and the number of DOF $f(q)$. The DOF of the developed regression model is calculated using row-wise matrix replication and expressed in Eq. (11).

$$f(q) = M(s-1) \tag{11}$$

The residual distribution $E_{ag}^2$ is calculated to modify the tolerability of the developed regression model using row-wise matrix replication and expressed in Eq. (12).

$$E_{ag}^2 = \frac{s\sum_1^M (q-q_x)^2}{M-n} \tag{12}$$

whereas $q$ represents the calculated index of the response variable, $M$ represents the index number in the regression matrix, $n$ represents the number of interrelated coefficients in the developed regression model.

During the design of civil engineering structures, the basis of the design of the experiment and statistical analysis comprises mathematical correlations between input and output variables such as raw material attributes and utilization and technical variables. This enables comprehensive monitoring and refinement of the technical process with lower capital costs and the creation of highly efficient building structures with the needed functionality. Thus, the developed regression mathematical model enables the interpolation and extrapolation functionalities, emphasizing monograms and realistic calculation of the response variables, considering the changes in the input variables.

## 4 INTEGRATED APPROACH FOR MONITORING THE CIVIL ENGINEERING STRUCTURES

Civil engineering structures degrade throughout time based on operating pressures and environmental impacts. Structural deterioration, such as fatigue induced by recurrent traffic loads, frequently occurs in civil structures. Meanwhile, large-scale episodic occurrences such as floods and earthquakes can produce significant structural destruction. Integrated sensor fusion devices with an optimized mathematical model-based damage detection system show potential for assessing damage mitigation to major civil engineering structures [28, 47]. These fault diagnosis approaches are widely classified into two types: information-based and prototype-based strategies. Information-based approaches use statistical analyses to assess the present status, but they may only identify the presence of deterioration. The prototype-based approaches require a verified actual physiological model of the structure for identifying and analyzing structural damage.

Although the area of structural health monitoring as implemented in civil engineering structures is in its early stages, it is already exhibiting significant benefits in assessing the stability of existing infrastructure and landscaping the way for sustainable development of structural behavior and the advancement of structural design. An integrated approach for monitoring the civil engineering structures is illustrated in Fig. 2.

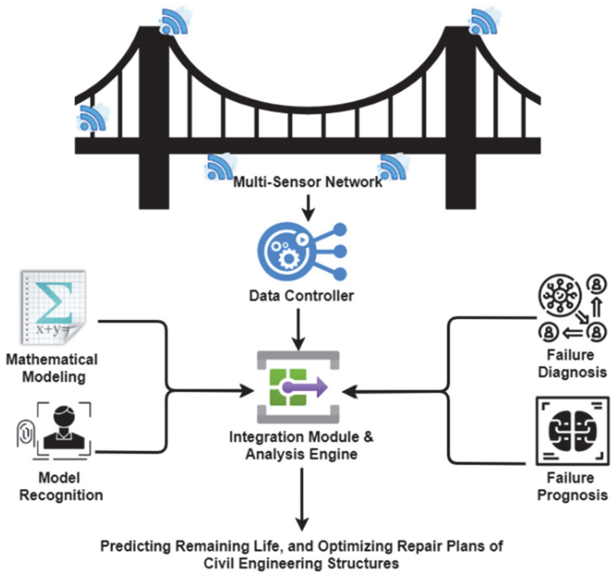

**Figure 2** Integrated monitoring system

Integrating intelligent sensing platforms with effective algorithms for real-time data processing provides valuable tools for assessing present conditions, predicting remaining life, and optimizing repair plans of civil engineering structures. The intelligent sensing platforms collect the civil structure data in real time, process it in the data synthesis module, and then transfer it to the integration module. The integration module is interconnected with mathematical modeling, model recognition, failure diagnosis, and failure prognosis. The analysis engine in the data integration can process the data received from various resources, predict the remaining life, and optimize repair plans of civil engineering structures.

The multi-sensor network information is sent to a data controller. Most of the sensors are intended to provide raw data that has not been analyzed at the structural site. Data controller units are generally used as data collectors and processors [49]. Currently, data transmission is accomplished using wireless communications. A well-designed sensor fusion system will include a data processor, which serves as the principal cognitive engine and the structural monitoring system's manager. Integration and compilation of encoded sensor data, manipulation and assessment of Structure relevant data, measurement, and determination of structural failure, and distribution of required comprehensive needs of the central facility to monitor and predict the remaining life and optimize repair plans of civil engineering structures. The information from the various sensors can be stored or retrieved by a data processor. Modern digital data collecting systems and wireless technology capabilities can enable quick information transmission from sensors to the data processor without the need for intrusive and insecure cables passing through civil engineering structures.

Numerous analytical tools may be included within the data processor, each allowing for assessing the overall structure's characteristics and functionality. The analytical tools are simulation tools, nonlinear finite element analysis, frequency calculations, and the correlation of observed structural quantities with key process parameters. If needed, the data processor may request any sensor for more data or do some rudimentary local analysis before transmitting the data. Decision instruments for selecting relevant communication signals to the central facilities can be included in the data processor's responsibilities. The central monitoring facilities are designed to collect and analyze damage signals from all monitoring network systems.

Furthermore, adopting a properly built monitoring system would provide a better comprehension of structural behavior through data analytics and interpretation. This would also result in improved and more detailed structural engineering approaches. As an outcome, all of these would contribute to advancements in the development and installation of civil structures, culminating in the establishment of a modernized area of intelligent civil engineering structures.

## 5 EXPERIMENTAL RESULTS AND DISCUSSIONS

This chapter discusses the significant performance of the developed integer linear programming mathematical model to divide building activities in a project to solve building planning problems. MMCE was introduced to complete an accurate and quick estimation of civil systems such as traffic networks, structural systems, and building projects, becoming more and more achievable through omnipresent sensor networks and communications systems over traditional civil engineering structure monitoring strategies like the capacitive imaging approach (CIA), eddy current pattern (ECP), multi-sensor network (MSN), and wireless sensor fusion (WSF). In this paper, civil engineering structure functionality data are gathered from 24 user nodes.

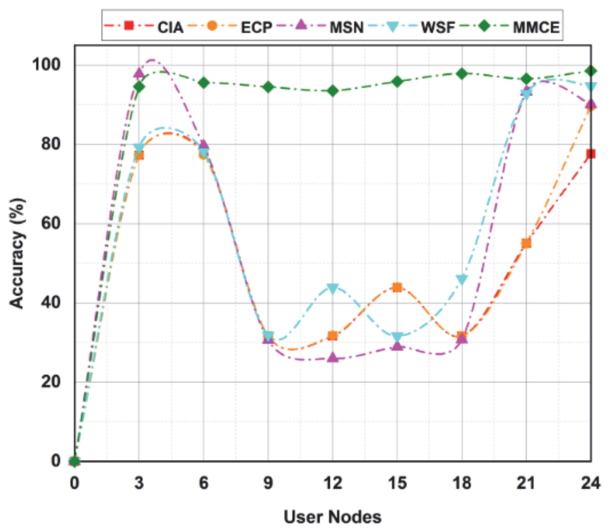


**Figure 3** Accuracy (User Nodes)

As illustrated in Fig. 3, the deployed framework (MMCE) is used to predict the remaining life and optimize repair plans of civil engineering structures. The deployed framework involves the integrated sensor fusion device with an optimized mathematical model-based damage detection system for assessing damage mitigation in major civil engineering structures. This framework integrates the sensor fusion network with an optimized mathematical model that efficiently monitors civil engineering structures.

In addition, the deployed framework uses the statistical, mathematical model for 16 monitoring intervals. The data processor is utilized for data collection, analysis, and storage functions, and it can maintain 2 TB of information with an analysis speed of 2.4 GHz. Furthermore, computational algorithms capable of retrieving useful data from historical information have been developed. Data fusion refers to the combination of data collected from numerous sensing systems and intelligence. The dependability of the data utilized inside the fusion mechanism will be determined by the sensors accessible and the methods utilized for data fusion. The choice of sensors, as the number of sensors required to improve the reliability of the information conveyed, is determined based on the solution needed. The experimental results of the deployed framework are assessed using the quality metrics like accuracy, confidence, reliability, and ambiguity. For evaluating the monitoring functionalities, predicting remaining life, and optimizing repair plans of civil engineering structures using the deployed framework (MMCE), a comparative investigation is executed on traditional civil engineering structure monitoring strategies like CIA, ECP, MSN, and WSF.

### 5.1 Accuracy Analysis

The deployed framework accuracy was considerably enhanced for varying user nodes and monitoring intervals, as shown in Figs. 3 and 4. Here, the initial state collects the civil and structural data from the wireless IoT sensor and analyzes whether the structure's condition is stable or unstable. Based on this analysis condition, the accuracy is improved, and this data is integrated with the wireless sensor fusion system and mathematical model.

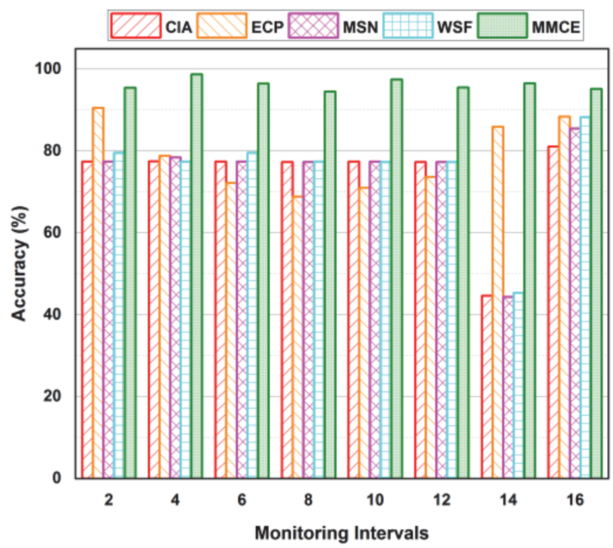


**Figure 4** Accuracy (Monitoring Intervals)

If any unstable movement is observed, the indication signal is transferred to the people who reside in the buildings, and it is equated as $\sum_{1}^{L}\left[\sum_{1}^{M} p_{jx}^{2} q_{x}\right]$. The data will be transmitted from the user nodes to the sensor fusion system. The response is identified as an indication signal. This indication signal is provided as per the plan, and the data related to the civil structures' condition is synchronized with the historical data. This match condition is validated on the integrated sensor fusion device with an optimized mathematical model, differentiating individual civil structure conditions on the buildings. The amount of collected data from the sensor fusion network is integrated with the mathematical model for categorizing stable or unstable conditions of civil engineering structures. In this evaluation, the accuracy of the monitoring device is improved, and the state of the civil engineering structure is accurately identified. If the condition of the civil structures is stable and as per the standards, the indication signal is not sent; otherwise, it is sent to the people residing in the buildings. The tracking conditions indicate the buildings' behavioral conditions and realistically identify the response.

## 5.2 Confidence Aspects

The confidence ratio was enhanced for varying user nodes and the monitoring intervals, as shown in Figs. 5 and 6.

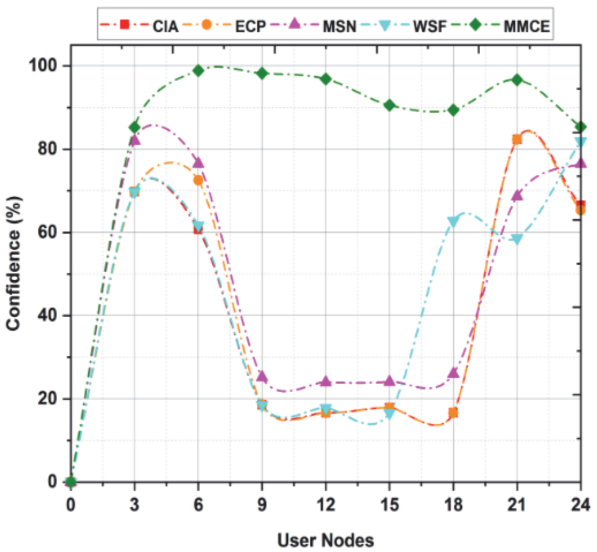

**Figure 5** Confidence (User Nodes)

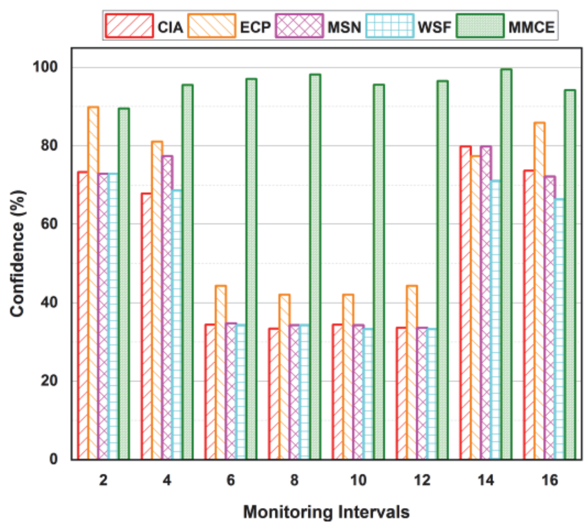

**Figure 6** Confidence (Monitoring Intervals)

Suppose the condition of the civil engineering structure is unstable. In that case, the data is developed from a smart sensor fusion network, and it is synchronized with the historical error values in the data processor. Whereas the information is analyzed, the warning is the indication signal to people residing in such buildings. In this manner, the confidence ratio is improved, and it is equated as $\sum_1^M p_{jx} p_{kx} q_x$, it is achieved through the identification module.

The deviation between stable and unstable data is detected at a quick and realistic processing state, and the responses are premeditated in real time. Therefore, the response proved that the civil engineering structures' conditions are in an emergency state and uncertain. Sensor fusion network information is traced frequently, and reliability and variability are observed during data analysis. Monitoring activity is completed in a realistic manner in this assessment system and is integrated into the continuous processing of responses. The historical data mapping and data analysis are performed utilizing the structural health monitoring arrangements. The confidence ratio is integrated with the mapping practice for the strategic assessment. The user nodes are used to transmit data and develop real-time responses from the smart sensor fusion network. Thus, user nodes identify the user requirement and their actions and progress a stronger indication signal as the response of the monitoring system.

## 5.3 Reliability Rate

The reliability rate for varying user nodes and monitoring intervals for the deployed framework and continuous monitoring of the civil engineering infrastructures are shown in Fig. 7 and Fig. 8. The sensor fusion network data is transmitted to the user nodes and controls the mapping parameter with the forecasted model expressed as $\frac{\sum_1^M \sum_1^s \left(q_{xj} - \overline{q_x}\right)^2}{M\left(s-1\right)}$. The transmitted data is classified as stable and unstable, and the forecasting response is integrated with the historical mapping.

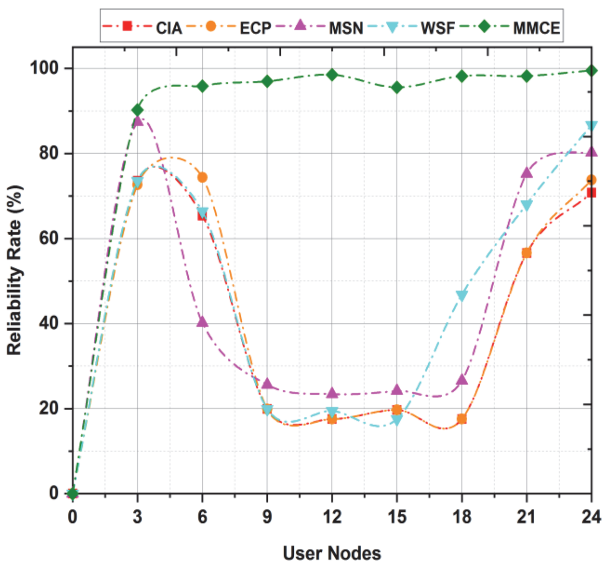

**Figure 7** Reliability Rate (User Nodes)

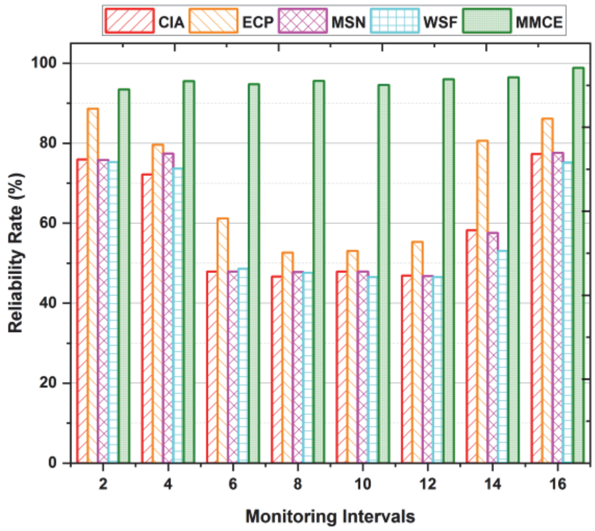


**Figure 8** Reliability Rate (Monitoring Intervals)

The forecasted model is related to the historical analyzing state and specifies the condensed cost to trace action. The service response is transferred on a schedule, and it produces a progressed level of precision. The deployed framework improves the reliability rate for several wireless sensor networks with the enhancement in precision. The deployed framework forms the smart sensor fusion network, the data is obtained and integrated, and it is used to identify civil engineering structure conditions and simulation response. The civil structure's condition is in this analyzing state as an emergency, and the reply from the analysis engine is given immediately.

### 5.4 Ambiguity Rate Analysis

The ambiguity rate for varying user nodes and monitoring intervals is reduced and illustrates more optimal responses than the traditional civil engineering structure monitoring strategies like CIA, ECP, MSN, and WSF, as shown in Fig. 9 and Fig. 10.

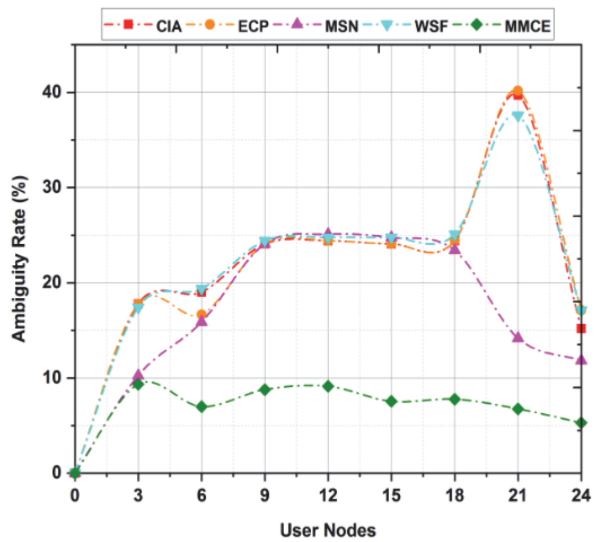


**Figure 9** Ambiguity Rate (User Nodes)

The utilization of the information collected from the historical data, the integrated sensor fusion network, and forecasted performance is expressed as $\frac{s\sum_{1}^{M}\left(q-q_x\right)^2}{M-n}$. Collected data is used through the opinion from indication signals and conditions of civil engineering structures. Here, a smart sensor fusion network is used, investigating a historical state is successively performed, and the responses are stored. The user nodes' information is used to predict data for integration with the historic match. The structure condition is monitored realistically for this use of collected information. This study uses the input system reference.

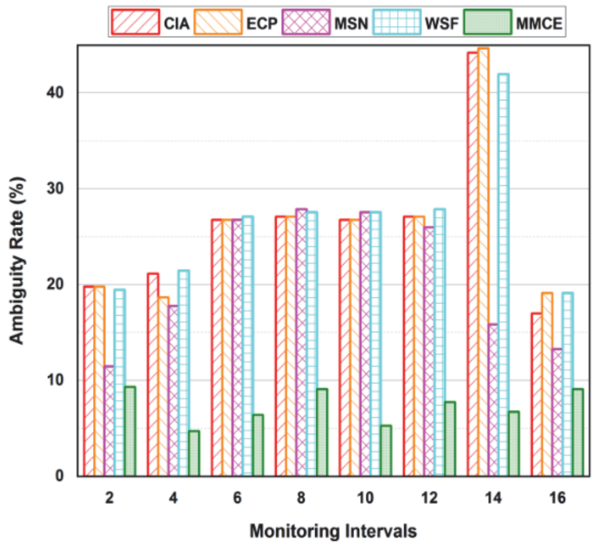


**Figure 10** Ambiguity Rate (Monitoring Intervals)

According to the preceding discussion, adopting a properly built monitoring system would provide a better comprehension of structural behavior through data analytics and interpretation. This would also result in improved and more detailed structural engineering approaches. As an outcome, all of these would contribute to advancements in the development and installation of civil structures, culminating in the establishment of a modernized area of intelligent civil engineering structures. The experimental results are listed in Tab. 1 and Tab. 2.

**Table 1** Experimental result for user nodes

| Quality Indicators | CIA | ECP | MSN | WSF | MMCE |
|---|---|---|---|---|---|
| Accuracy / % | 77.74 | 89.66 | 97.76 | 94.73 | 99.50 |
| Confidence / % | 82.35 | 82.35 | 82.01 | 81.90 | 98.89 |
| Reliability Rate / % | 73.58 | 73.80 | 87.41 | 86.74 | 99.52 |
| Ambiguity Rate / % | 15.19 | 16.65 | 10.24 | 17.10 | 5.29 |

Tab. 1 details the deployed framework's quality metrics responses (MMCE) comparatively with the traditional civil engineering structure monitoring strategies for user nodes. The comparison of experimental results with similar data is shown in reference [50]. The deployed framework (MMCE) provides enhanced results in all quality metrics with the traditional civil engineering structure monitoring strategies like CIA, ECP, MSN, and WSF. Based on the comparative analysis deployed framework with traditional approaches, the deployed framework provides enhanced accuracy, confidence, and reliability and reduced ambiguity rate by 21.86%, 16.73%, 26.07% and 69.06%, respectively.

**Table 2** Experimental result for monitoring intervals

| Quality Indicators | CIA | ECP | MSN | WSF | MMCE |
|---|---|---|---|---|---|
| Accuracy / % | 81.11 | 90.56 | 85.50 | 88.31 | 98.74 |
| Confidence / % | 73.69 | 89.89 | 79.88 | 72.90 | 99.52 |
| Reliability Rate / % | 77.29 | 88.65 | 77.63 | 75.26 | 98.89 |
| Ambiguity Rate / % | 16.99 | 18.68 | 11.48 | 19.13 | 4.73 |

Tab. 2 details the deployed framework's quality metrics responses (MMCE) comparatively with the traditional civil engineering structure monitoring strategies for monitoring intervals. The deployed framework (MMCE) provides enhanced confidence, reliability, and ambiguity outcomes by 98.74%, 99.52%, 98.89%, and 4.73%. Simultaneously, the CIA framework for monitoring intervals provides poor outcomes. Based on the comparative analysis deployed framework with traditional approaches, the deployed framework provides enhanced accuracy, confidence, reliability rate and reduced ambiguity rate by 17.86%, 25.96%, 21.84% and 75.27%, respectively.

## 6 CONCLUSION

This research explores various recent data fusion applications in civil engineering (CE) and presents some potential advantages of data fusion in civil engineering. In this article, an integer linear programming mathematical model is developed to divide building activities to solve building planning problems. The adoption of a properly established monitoring system will provide a better understanding of structural behavior through data analysis and interpretation. This will also lead to improved and more detailed structural engineering methods. Therefore, all of this will contribute to progress in the development and installation of civil structures, ultimately establishing a modern field of intelligent civil engineering structures. The experimental results show that the system has a high accuracy of 99.50% and the lowest ambiguity rate of 4.73% compared to traditional approaches. In all, the reliability of the developed framework gives the enhanced outcome of 99.52%.

## Acknowledgments

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**Contact information:**

**Jianling TAN**
(Corresponding author)
School of Civil Engineering and Transportation Engineering,
Yellow River Conservancy Technical Institute,
Kaifeng, 475004, China
E-mail: htanjl_2023@163.com

**Dan LI**
School of Civil Engineering and Transportation Engineering,
Yellow River Conservancy Technical Institute,
Kaifeng, 475004, China
E-mail: 986394895@qq.com