



INTELLIGENT DIGITAL TWIN-BASED PREDICTIVE LIFECYCLE MANAGEMENT OF MODULAR REINFORCED CONCRETE STRUCTURES USING ARTIFICIAL INTELLIGENCE AND REAL- TIME STRUCTURAL MONITORING

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Abstract

The ever-growing complexity of modular reinforced concrete structures requires the development of intelligent and continuous solutions for structural monitoring and management of their lifecycle. Conventional approaches to inspections and maintenance of structures are usually performed in a periodic manner and may not provide sufficient information regarding the developing processes of deterioration and future structural performance. An Intelligent Digital Twin-Based Predictive Lifecycle Management Framework that utilizes Artificial Intelligence (AI), Internet of Things (IoT), Digital Twin, and real-time Structural Health Monitoring (SHM) is proposed in this research. The suggested framework introduces continuous interaction between the physical structure and its digital twin by means of monitoring the mentioned parameters via sensors. The gathered data are further processed and normalized, then transformed into the structural health indicators that will be analyzed with the use of AI-based predictive models. The predicted structural responses will be used together with Digital Twin for anomaly detection, assessment of the structural condition, and planning of the predictive maintenance actions. The Structural Condition Index is proposed for classification of the structural conditions and maintenance prioritization. The framework allows for both global and component-based assessment with a special focus on critical modular connections. In conclusion, the introduced approach

provides the transition from reactive and periodic maintenance towards continuous predictive and condition-based management of the modular reinforced concrete structures.

Keywords: *Digital Twin, Artificial Intelligence, Structural Health Monitoring, Modular Reinforced Concrete, Predictive Maintenance.*

1. INTRODUCTION

Structures of modern infrastructure require ongoing evaluation to make sure that they are safe, durable, reliable, and efficiently maintained during their operational lifetime. The combination of digital technologies with structural engineering presents many chances to monitor physical structures in real time and forecast their state in the future. Digital Twin technology along with artificial intelligence and structural health monitoring may be viewed as a prospective solution for this transformation.

1.1 Background

In the construction sector, AI, IoT, BIM, sensor technology, and DT are some of the technologies that have been embraced in recent times. Classical structural health management relies heavily on inspection and maintenance schedules, which may fail to identify deterioration occurring between inspection times. In the case of reinforced concrete, some of the factors that may affect such structures include cracking, corrosion, carbonation, fatigue, deformation, and ageing. Real-time Structural Health Monitoring (SHM) provides real-time information about changes taking place within such structures via measurements like strains and displacements among others.

1.2 Modular Structures and Digital Twins

Modular reinforced concrete construction provides fast building process, quality assurance, and low wastage of materials. Yet, transport, assembling process, different deformations, and connections between modules might impact the performance of the structure for a long time. The Digital Twin approach can resolve the mentioned problems through generating dynamic digital model of a physical object and including all necessary data into the model.

1.3 AI-Based Predictive Management

The use of AI allows the Digital Twin to analyze real-time as well as historical data for detecting any abnormality as well as predicting future deterioration of the structure. The collected data can be subjected to some noise, missing values, outliers as well as environmental influences. Hence, proper pre-processing and intelligent analysis of data is needed.

1.4 Research Problem and Contribution

Traditional life-cycle management could be reactionary, time-consuming, and based on maintenance schedules. The proposed research integrates the following life-cycle management framework: real-time monitoring, IoT, digital twin, artificial intelligence prediction, and condition-based maintenance. The proposed process includes the following steps:

Physical Structure → Sensors → Data Analysis → Digital Twin → Artificial Intelligence Prediction → Condition Evaluation → Maintenance

The proposed framework will help in the assessment of the whole structure as well as the connections between modules.

1.5. Research Objectives

The research goals of the present study are listed below:

- Development of an intelligent Digital Twin model of modular reinforced concrete structures using the concept of real-time Structural Health Monitoring, IoT sensing, and structural data.
- Development and validation of AI-based prediction models to identify anomalous structural behavior and predict the future state and degradation of modular reinforced concrete structures.
- Condition evaluation and assessment of critical joints in modular reinforced concrete structures using real-time monitoring data and AI-based predictions.

- Establishment of a predictive life-cycle management methodology for condition-based inspection and maintenance of modular reinforced concrete structures.

2. REVIEW OF LITERATURE

Mahmoodian et al. (2022) dedicated to the development of a Digital Twin framework to enable intelligent maintenance of civil infrastructure. The authors have analyzed the integration of Digital Twin technology into infrastructure monitoring and maintenance operations. According to the researchers, traditional maintenance had involved periodical inspections and scheduling that could lead to the delayed detection of degradation and the inefficient allocation of maintenance resources. As part of their framework, the authors had introduced infrastructure information, monitoring information and maintenance processes to the digital space. The results obtained by the researchers have suggested that Digital Twin technology has improved condition monitoring, facilitated predictive maintenance and lifecycle decision-making. Thus, the article provided a valuable foundation for the implementation of Digital Twin technology in infrastructure management.

Pecora (2022) studied the usage of Digital Twin technology for condition monitoring of a cold stamping machine. Specifically, he focused on the creation of a digital model of the machine and the continual flow of operational information into the digital environment. As a result, the researcher has shown that Digital Twin technology enabled real-time condition evaluation and detection of abnormal operation of the device. Moreover, the research proved that continuous monitoring could contribute to more timely maintenance decisions. Even though the research was dedicated to an industrial machine, its findings highlighted the potential of Digital Twins in real-time monitoring and predictive maintenance of other engineering facilities.

Wang et al. (2021) examined the implementation of Artificial Intelligence in Product Lifecycle Management. Specifically, the researchers have explored the ways in which various AI methods could be utilized at different lifecycle stages including design, production, operation, maintenance, and decision-making. The researchers have noted that AI technologies enabled the processing of huge amounts of data, pattern recognition, prediction, and intelligent decision-making. As stated by the researchers, AI has enabled the shift of lifecycle management from information management to more

predictive processes. Thus, these findings were relevant to structural lifecycle management because the similar approach could be used to predict deterioration and maintenance.

Warke et al. (2021) considered the application of the Digital Twin concept in the sustainable development of smart manufacturing. Using statistical analysis, the researchers had studied the role of Digital Twin solutions in intelligent manufacturing processes. The results showed that the use of Digital Twins had led to increased monitoring capabilities, process optimization, resource usage, and operational decisions. Moreover, it had been shown that continuous interaction between the physical and digital representation of the physical systems could increase the efficiency of lifecycle operations. While the study had concentrated on manufacturing, its results had provided valuable evidence for applying Digital Twin concepts to the lifecycle management of infrastructure.

Yu and He (2022) considered the application of the Digital Twin concept in disaster prevention and mitigation of risks in infrastructure. In this study, the development, challenges, and future directions of the application of Digital Twins in the management of infrastructure risks were analyzed. It was found out that Digital Twins allowed integrating real-time monitoring, information about infrastructure, simulation, and intelligent analysis. Thus, they provided enhanced situational awareness and early detection of possible risks. However, the research identified challenges associated with data integration, modeling accuracy, system complexity, and real-time implementation.

The above-stated studies had emphasized the role of Digital Twins and AI technology in monitoring, prediction, maintenance, lifecycle management, and the resilience of infrastructure. However, limited research had concentrated on the combination of real-time Structural Health Monitoring, AI-based prediction, Digital Twin, and predictive lifecycle management for the case of modular reinforced concrete structures. In this research, this gap is being addressed through an integrated framework where real-time structural data are synchronized with a Digital Twin and analyzed by AI-based models.

3. RESEARCH METHODOLOGY

The current study employed an approach that involved both computations and monitoring in order to create an Intelligent Digital Twin-Based Predictive Lifecycle Management Framework for Modular Reinforced Concrete Structures. This framework included the use of real-time SHM (Structural Health

Monitoring), IoT (Internet of Things), Digital Twins, Artificial Intelligence, data pre-processing, prediction models, evaluation of the condition of structures, and maintenance decisions. The entire research process was geared towards creating interaction between the actual structure and the digital model.

3.1 Research Framework and Digital Twin Development

The proposed framework followed a continuous information flow:

Physical Structure → Sensor Network → Data Acquisition → Data Processing → Digital Twin → AI Prediction → Condition Assessment → Maintenance Decision

A digital twin of the physical modular reinforced concrete structure was established through a Digital Twin that involved data pertaining to structural shape, material characteristics, modular elements, connection, loading, sensors and past performance of the structure. The difference between the proposed Digital Twin and a static digital model was that the Digital Twin was updated using real-time monitoring data.

The reason why this framework focused on modular elements and their connections is that such elements could be subjected to various kinds of deformations, connection displacements, stress concentrations and others throughout the service life. Therefore, each element was associated with relevant monitoring data.

3.2 Real-Time Monitoring and Data Processing

Real-time SHM was the main source of data for the proposed framework. Sensors were deployed at strategic points on the structure to measure parameters such as strain, displacement, acceleration, vibration, temperature, humidity, cracking, and joint behavior. The monitoring vector at time t was expressed as:

$$X_t = [\epsilon_t, d_t, a_t, v_t, T_t, H_t, C_t]$$

where ϵ_t represented strain, d_t displacement, a_t acceleration, v_t vibration response, T_t temperature, H_t humidity, and C_t a crack or deterioration indicator.

The sensor network sent the observations using a data acquisition system enabled with Internet-of-Things. The observations had timestamps and were tagged with the ID of the sensor. This made sure that the Digital Twin had an updated model of the structure's behaviour.

The data underwent pre-processing before any analysis was done. Missing values, noise, outliers, transmission errors, and sensor drift were accounted for. If needed, normalization was carried out using:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Feature engineering followed in order to extract meaningful structural features such as mean and maximum strain, displacement rate, vibration change, crack growth rate, and joint deformation. Changes over time were captured through:

$$R_t = \frac{Y_t - Y_{t-k}}{k}$$

This process converted raw monitoring observations into structured variables suitable for predictive analysis. Detailing sensor calibration methods Edge computing for data processing expand on feature engineering steps.

3.3 AI-Based Prediction and Structural Condition Assessment

AI models were utilized for establishing relations between monitoring parameters and structure behavior as well as predicting future structural behavior. Linear Regression, Random Forest, Gradient Boosting, Support Vector Regression, Artificial Neural Network, and LSTM models could be applied based on the nature of the monitoring data.

General prediction relation can be represented as:

$$\hat{Y}_{t+1} = F(X_t, X_{t-1}, \dots, X_{t-k})$$

For sequential structural data, LSTM-based modelling was considered particularly suitable because it could capture temporal dependencies in structural behaviour.

Model performance was evaluated using MAE, RMSE, and R^2 :

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2}$$

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

The difference between observed and predicted behaviour was subsequently used for anomaly detection:

$$e_t = |Y_t - \hat{Y}_t|$$

Persistence of elevated prediction errors was considered as a possible sign of anomalous behavior of the structure. Nonetheless, environmental influences and sensor measurement errors were taken into account before declaring any abnormality in deterioration.

A Structural Condition Index (SCI) was developed to aggregate various structural health parameters:

$$SCI_t = \sum_{i=1}^m w_i Z_{i,t}$$

where $Z_{i,t}$ represented normalized structural-health indicators and w_i represented their corresponding weights.

The resulting structural condition could be categorized as Healthy, Caution, Warning, Critical, or Emergency, with corresponding monitoring, inspection, and maintenance actions.

3.4 Predictive Lifecycle Management and Validation

The last phase involved changing the structural predictions to maintenance decisions. This was based on structural status, deterioration predictions, criticality, and urgency of the structure. Conceptually, the maintenance-priority equation could be stated as:

$$MP = f(D, R, C, T)$$

where D represented predicted deterioration, R structural risk, C component criticality, and T predicted intervention time.

Those components that exhibited stable behavior were kept under routine monitoring while those components that exhibited abnormal behavior were focused on inspection.

Inspection or maintenance data was fed back into the Digital Twin after the process was done. It established a continual life cycle loop:

Monitor → Analyse → Predict → Assess → Maintain → Re-monitor → Update

Therefore, the above-discussed methodology involved the integration of real-time monitoring, artificial intelligence forecasting, Digital Twin, and condition-based maintenance into one lifecycle management system. The purpose of the methodology was to help detect the wear and tear of the structure at an earlier stage and make maintenance planning more effective and efficient.

4. DATA ANALYSIS AND INTERPRETATION

The stage of data analysis and interpretation aimed at assessing the performance of the suggested Intelligent Digital Twin approach in predicting the condition of modular reinforced concrete structures. The data analysis included structural monitoring parameters, data pre-processing, AI-based prediction, anomaly detection, and structural condition assessment. The findings have been interpreted considering the aspect of real-time monitoring and life-cycle prediction management.

4.1 Structural Monitoring Data Analysis

The monitoring system involved the use of parameters like strain, displacement, acceleration, vibration, temperature, humidity, and connection behavior. The choice of these parameters was due to the fact that they had information on the performance of the structure. Strain and displacement were static and deformation-based, respectively, whereas acceleration and vibration were parameters related to dynamic performance of the structure.

Table 1: Structural Monitoring Parameters and Their Interpretation

Monitoring Parameter	Structural Information	Interpretation
Strain	Stress and deformation response	Increasing abnormal strain may indicate excessive loading or deterioration
Displacement	Structural movement	Persistent increase may indicate deformation or loss of stiffness
Acceleration	Dynamic response	Changes may indicate altered structural behaviour
Vibration	Dynamic characteristics	Frequency changes may indicate stiffness variation
Temperature	Environmental influence	Used for environmental compensation
Humidity	Exposure condition	Supports deterioration assessment
Connection Response	Modular interface behaviour	Helps identify connection-level abnormalities

This analysis revealed that no single parameter used for monitoring purposes could give a complete description of the structural condition. Rather, a combination of several parameters gave a better picture of the structure's behavior. For modular structures, parameters describing connections were especially useful as degradation could happen locally before being evident globally.

4.2 Data Preprocessing and Feature Analysis

Prior to employing any predictive models, the monitoring data was first subjected to quality checking. The missing data, abnormality, sensor noise and sensor inconsistency issues were checked. The environmental factors were also taken into account due to the potential effects of temperature and

humidity on the structures. Through normalization, variables of different unit types and scale could be compared. The feature engineering step further refined the raw observations into structural indicators.

Table 2: Data Preprocessing and Feature-Engineering Results

Data Processing Stage	Variables/Features	Analytical Purpose
Data validation	Sensor readings, timestamps	Identification of invalid observations
Missing-value treatment	Strain, displacement, vibration	Maintaining continuity of monitoring data
Outlier detection	Extreme sensor observations	Separation of sensor errors from structural events
Normalization	All numerical variables	Establishing comparable measurement scales
Environmental adjustment	Temperature, humidity	Reducing environmental influence
Feature extraction	Mean, maximum, variation	Describing structural response
Trend analysis	Rate of change	Identifying deterioration progression

The process of data preprocessing increased the consistency and clarity of the monitoring data set. The data features were much more appropriate for processing by an artificial intelligence algorithm than the initial readings of the sensors as the features included both current behavior and trends. This was essential for predictive lifecycle management as both direction and rate of degradation were crucial.

4.3 AI Model Performance and Prediction

The processed data set was used to construct the prediction models that used artificial intelligence techniques. The accuracy of the prediction model was done through comparing predicted responses with observed monitoring responses. The metrics used to evaluate prediction errors included MAE and RMSE, while was used to evaluate agreement.

Table 3: AI Model Evaluation Framework

Model	Analytical Function	Evaluation Measure	Expected Interpretation
Linear Regression	Baseline prediction	MAE, RMSE,	Establishes a reference performance
Random Forest	Nonlinear prediction	MAE, RMSE,	Captures complex variable interactions
Gradient Boosting	Predictive modelling	MAE, RMSE,	Improves nonlinear prediction
Support Vector Regression	Response prediction	MAE, RMSE,	Effective for complex relationships
Artificial Neural Network	Nonlinear learning	MAE, RMSE,	Learns complex structural patterns
LSTM	Time-series prediction	MAE, RMSE,	Captures temporal deterioration patterns

From the comparative analysis, it became apparent that AI techniques can offer a suitable means of capturing complex relationships between structural variables and their environment. Traditional regression analysis offered an adequate starting point, but where the structural behavior depended on a combination of different factors, non-linear approaches would be better suited. The use of LSTM modeling was relevant to life-cycle prediction as it took into account the history of the variable being

predicted. The results of the modeling were interpreted based on the value of the prediction residuals. Small and stable residuals meant that the structural behavior is consistent with the expected condition while a growing residual meant a possible change in the structural behavior. Prediction accuracy was therefore considered from the perspective of both error magnitude and behavior.

4.4 Structural Condition Assessment and Lifecycle Interpretation

The expected and measured structural responses were combined in a Structural Condition Index (SCI). The SCI offered an aggregated measure of the structural condition, where several normalized measures were combined. The assessment included current condition, severity of anomalies, persistence of the abnormality, and expected future deterioration.

Table 4: Structural Condition Classification and Maintenance Interpretation

Condition Level	Structural Behaviour	Digital Twin Interpretation	Recommended Action
Healthy	Stable and expected response	Normal condition	Routine monitoring
Caution	Minor deviation	Early change detected	Increase monitoring frequency
Warning	Persistent abnormal response	Potential deterioration	Targeted inspection
Critical	Significant deterioration	High-risk condition	Preventive intervention
Emergency	Severe or rapidly increasing abnormality	Immediate risk	Immediate engineering assessment

The example of classification of condition showed how the Digital Twin that is being suggested will help to turn the data from the monitoring system into useful information throughout the life cycle. The

structurally healthy object could be left under normal monitoring, while the object at warning level should be subject to physical check. If there is a critical or an emergency condition, it should be addressed immediately through engineering.

It should also be noted that the component-level assessment is important. There may be such a situation when a modular connection is deformed or vibrates abnormally, but the object itself behaves acceptably. Such changes could be detected by the Digital Twin, since each monitoring node corresponds to a particular structural component.

Overall interpretation of the proposed approach may be presented as:

Real-Time Monitoring → Data Processing → AI Prediction → Anomaly Detection → Structural Condition Assessment → Predictive Maintenance

The framework hence facilitated the move from traditional reactive maintenance to condition-based and predictive lifecycle management. Rather than wait until deterioration is observable or simply follow fixed time-based inspection schedules, maintenance could now be based on continually refreshed structural data and future prediction.

Another benefit was the feedback process post-maintenance. After maintenance was complete, new sensor data could be fed into the Digital Twin model and compared with the status prior to the maintenance action. This would facilitate an assessment of the success of maintenance and provide refreshed data for future AI predictions.

In summary, the data analysis framework showed that the combination of real-time monitoring, AI prediction, and the use of Digital Twins provided a complete framework for the assessment of the structure's condition. It was particularly applicable for reinforced concrete modular structures as it allows for both global assessment of the structure and localized assessment of important components and connections.

5. CONCLUSION

In the current study, an Intelligent Digital Twin-based Predictive Life-cycle Management Framework was suggested for modular reinforced concrete structures through the combination of Artificial

Intelligence (AI), IoT, Digital Twin concept, and real-time SHM systems. This framework was designed to overcome the limitations of traditional structural management that mostly relies on inspections, evaluations, and maintenance schedules. Real-time parameters including strain, displacement, vibration, acceleration, temperature, humidity, and behavior of modular connections were considered in order to evaluate structural condition in a timely manner. Pre-processing and feature extraction procedures were utilized to conduct reliable analysis, while the use of AI-based prediction made it possible to detect any abnormal behavior or deterioration in the future. The integration of these results into Digital Twin will make it possible to conduct continuous structural condition evaluation and develop maintenance plans based on the results. In general, the proposed concept represents a transition from reactive maintenance towards predictive and condition-based life-cycle management through continuous monitoring, analysis, prediction, assessment, and updating. Nevertheless, AI predictions need to be backed up by professional engineering expertise, inspections, and structural codes. Further research should concentrate on monitoring data, experimentation, uncertainty analysis, and remaining useful life predictions.

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