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Internet of Things based Durability Monitoring and Assessment of Reinforced Concrete Structures

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Abstract

We present a conceptual framework for continuous in-service durability monitoring and assessment of reinforced concrete (RC) structures. Conventional durability assessments are carried out through laboratory testing of samples taken destructively from the structures, which are labor intensive, time consuming and costly. By employing internet of things, continuous nondestructive in-service monitoring of structures can be realized in a cost-effective manner. The availability of long-term monitored data along with the use of intelligent data analysis enables capturing of the complex nonlinear interaction of durability controlling parameters, making the structures' condition assessment more reliable. The reliability of the assessment results is highly beneficial for stakeholders to plan proactive maintenance, which in turn extends the service life of the structures.

Keywords: IoT, intelligent data analysis, RC structures, durability, corrosion monitoring and assessment

1. Introduction

Civil infrastructure, such as buildings, bridges, and dams, are the backbone of the global economy where the majority of the infrastructure are made of reinforced concrete (RC) structures. These structures contributed 36 trillion USD to global gross domestic product (GDP) in 2016 [1]. This accounts for about 47% of the total GDP [2]. However, most of the infrastructure in the industrialized countries suffer from severe level of degradation. For instance, in 2017, the American Society of Civil Engineers evaluated the performance of the overall US infrastructure and grade it as D+ (poor, at risk), which is only one step above from the least grading class F (failing/critical, unfit for purpose)[3]. One of the main causes for the degradation is corrosion of reinforcement steel. Several studies revealed that corrosion related maintenance and repair of RC structures cost multibillion USD per annum globally. The conventional cor-

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rosion condition evaluation method usually involves periodic laboratory testing on samples taken destructively from the structure. This process is time-consuming, labor intensive, and costly. The maintenance plan is determined based on the output of empirical model, which uses the laboratory test results as input. The models entails several assumptions and simplifications, causing uncertainty in its results. These shortcomings call for reliable, cost-efficient, and nondestructive in-service corrosion assessment technique. Today, different types of low-cost sensors are available for continuous nondestructive monitoring of various real-life applications. One relevant example is structural health monitoring [4]. However, the existing structural health monitoring systems concentrate mainly on measuring the response of the structure to ambient and forced excitation, but not on the durability aspects of the structure.

In this work, the applicability of data-driven smart RC structure concept for durability assessment of RC structures is explored and conceptual framework is proposed. The framework employs internet of things and intelligent data analysis technique to monitor the corrosion causing factors and estimate the time to onset of corrosion without the use of empirical models. By performing intelligent data analysis on the collected long-term data, capturing the concrete's microstructure changes caused by time-dependent chemical processes of the cement paste and its interaction with the environment is achievable. This is beneficial to devise reliable maintenance plan proactively. In addition, the discovered knowledge on how the concrete microstructure alters with time and exposure conditions assist material scientists to design concrete that resist corrosion causing factors. The proposed framework enables inexpensive and convenient corrosion condition assessment without laborious involvement of human. The contributions of this work are: 1) a review of state-of-the art sensing methodologies for corrosion causing factors, 2) a survey on the use of intelligent data analysis technique in concrete durability assessment, and 3) a conceptual framework for realizing data-driven durability assessment.

The paper is organized as follows. In Section 2, conventional corrosion condition assessment methods including prediction of corrosion initiation time is discussed. The details of the proposed IoT based corrosion monitoring method, including sensors, and wireless technologies are presented in Section 3. The power of intelligent data analysis techniques for prediction of time to onset of corrosion and knowledge discovery are explained in Section 4. The proposed conceptual framework for realizing data-driven smart structure is presented in Section 5. Finally, the conclusion is provided in Section 6.

2. Conventional corrosion assessment approach

Corrosion of reinforcement steel in concrete is mainly initiated due to the penetration of carbon dioxide and/or chloride ions into the concrete pore solutions. Structures are susceptible to chloride attack if they are exposed to marine environment or deicing salt containing chloride. Carbonation[1]- and chloride-induced corrosion may result in considerable depletion in the load-bearing capacity of the structure by diminishing the cross-sectional area of the reinforcement steel, degrading its elongation capacity and causing severe cracking to the concrete. Cracked concrete exacerbate the corrosion further by allowing additional entry of oxygen, moisture, CO_2 and chloride ions into the concrete, affecting considerably the strength, safety and serviceability of the structure.

The corrosion process is normally divided into two stages: initiation and propagation. The corrosion initiation stage due to carbonation corresponds to the time required for the carbonation front to reach at the surface of reinforcement steel. In case of chloride, the corrosion initiation stage corresponds to the period for the chloride ions concentration to reach at a certain threshold level that triggers corrosion. The corrosion initiation period is often utilized to define the service life of RC structures [5, 6]. Periodic measurement of carbonation depth and/or chloride profile is vital for early corrosion detection and making well-informed decision regarding maintenance plan.

Conventional methods for measuring the carbonation depth and chloride profile of concrete involves chemical or physical laboratory techniques by extracting samples from in-service structures. These methods are often destructive and incur high costs (direct and indirect). For example, traditional in-service inspection and maintenance programs of highway structures cause traffic delay, which accounts for 15% to 40% of the construction costs [7]. After determining the carbonation depth and chloride profile from the samples, the remaining service life of the structure is evaluated

[1] Natural physicochemical process caused by the ingression of carbon dioxide (CO_2) from the neighboring environment into the concrete through pores in the matrix where the CO_2 reacts with hydrated cement.

using empirical models. These models are based on Fick's second law of diffusion and entails several simplifications and assumptions, causing substantial uncertainty in determining time to corrosion initiation [8]. This uncertainty could have severe impact on planning of inspection and maintenance, which may affect the service life of the structure adversely and increases the associated life-cycle costs. These shortcomings of the conventional carbonation depth and chloride ions concentration measurement methods call for cost-effective and nondestructive monitoring systems. Reliable assessment methods are also vital for making effective maintenance plan.

3. IoT based corrosion monitoring system

The blend of digital technology that comprises IoT based systems and advanced data analysis techniques with physical civil infrastructure has already given rise to the concept of structural health monitoring. Sensory data that are collected from multiple networks of distributed sensors can be analyzed, interpreted and delivered as reliable, robust and meaningful information to infrastructure providers, who can then perform well-informed decisions regarding the structural health and maintenance of their assets. The existing implementations of IoT based structural health monitoring systems target only load related physical impacts on the structure. But the structural health can also be deteriorated due to chemical attacks (e.g. carbonation and chloride ion penetration). Monitoring of the chemical attacks, especially for structures which are exposed to aggressive environment, is important for early deterioration detection.

As in structural health monitoring systems, IoT based monitoring of corrosion causing chemicals is beneficial. IoT based corrosion monitoring systems can be deployed in structures by embedding relevant sensors in the concrete in order to continuously measure the parameters that cause/accelerate corrosion of reinforcement steel. Measuring such parameters continuously using sensors will provide up to date knowledge about the status of the structure. The monitored data are communicated to the remote infrastructure service provider using appropriate wireless communication technologies.

3.1. Sensors

As carbonation decreases the alkalinity[2] of the concrete pore solution, measuring the pH allows to detect whether carbonation took place or not. Sensors that are able to measure pH and chloride content in the concrete can provide information regarding the condition of the embedded reinforcement steel, and thus it can be used as early warning system. Sensing technologies for monitoring the pH of concrete pore solutions and the amount of chloride ions in it are found in the literature [9, 10, 11, 12, 13, 14, 15]. The relevant sensing devices that are developed in the past 10 years can be classified into two main categories: potentiometric and fiber optic. Though a number of potentiometric electrodes exist in the area of analytical chemistry for examining ionic concentration, electrodes that are targeted for concrete environments are limited. $Ag/AgCl$ electrodes are the most widely used one [16, 17]. In case of pH monitoring, Ir/IrO_2, Ag/Ag_2O, Ti/IrO_2 and metallic oxide are the commonly used potentiometric electrodes. Two fiber optic based chloride ion sensing devices in concrete environment are found in the literature. One is based on suspended-core optical fiber [18] and the other one uses chloride ion sensitive fluorescence indicator dye [19]. The fiber optic pH sensing device based on pH sensitive optic fluorescence polymer has been proposed by Nguyen et al. [15]. The performance of all the sensors have been evaluated in various test environments (simulated concrete pore solution, mortar and concrete) for up to the period of two years. Almost all the studies concluded that the sensors are sufficiently accurate and stable. As the lifetime of RC structures spans about 50 to 80 years, the embedded sensors should be durable for much longer than two years, and easily replaceable, whenever necessary. In Table 1, the relevant details of the sensors that are tested for more than 6 months are presented.

3.2. Low-power wireless communication technologies

The communication method of the embedded sensors has impact on the flexibility and cost of the IoT based corrosion monitoring system. The sensors presented in the above subsection were mainly intended for sensing and

[2] Reduction of alkalinity results in depletion of the passive oxide layer of reinforcement steel, which eventually initiate corrosion.

Table 1. pH and chloride ion sensors for concrete structures.

Ref	Sensed parameter	Sensor category	Test environment	Exposure time
[9]	Chloride ion	Potentiometric ($Ag/AgCl$)	Simulated concrete pore solution	> 6 months
[10]	Chloride ion	Potentiometric ($Ag/AgCl$)	Concrete	12 months
[11]	Chloride ion	Potentiometric ($Ag/AgCl$)	Simulated concrete pore solution	24 months
[12]	pH	Potentiometric (IrO_x)	Concrete	24 months
[13]	pH*	Potentiometric (metallic oxide)	Cement paste	12 months
[13]	Chloride ion*	Potentiometric ($Ag/AgCl$)	Cement paste	12 months
[14]	pH*	Potentiometric (Ti/IrO_2)	Concrete	7.5 months
[14]	Chloride ion*	Potentiometric ($Ag/AgCl$)	Concrete	7.5 months
[15]	pH	Fiber optic (fluorescence polymer)	Concrete	20 months

* Integrated with other sensors.

transferring the measurement to datalogger through cables. The wired connection incurs high cost for installing and maintaining the monitoring system, especially to install it in spatially dispersed concrete elements. It is also inflexible and unattractive aesthetically. There have been few attempts for monitoring chloride ions with potentiometeric electrodes wirelessly [20, 21]. However, the proposed approaches were limited to very short distance communication (inductive coupling and RFID), requiring close range readings and thus are not suitable for continuous long-term durability monitoring of concrete structures.

Various low-power wireless communication technologies for IoT applications are available [23, 22, 25, 27, 28] and their practical use was demonstrated in several application test-beds. These technologies often differ in their characteristics, such as communication range, power consumption, data rate, and latency. They can be classified either based on their communication range (short- vs long-range) or the spectrum type (licensed vs unlicensed). Short-range wireless communication technologies, such as ZigBee [22], Bluetooth Low Energy (BLE) [23], and WirelessHART [24], require multi-hop mesh networking to cover a larger area. Most of these technologies operate in the 2.4GHz unlicensed ISM band, which often exhibit high loss and congestion.

Long-range low-power wireless communication technologies (e.g. LoRaWAN [25], Sigfox [28], and Narrowband IoT [26]) are often configured in star topology and form low-power wide area networks (LPWANs). Currently, LPWANs are gaining more attentions from the research community due to their ability to offer low-cost and massive connectivity over a wide geographical area. Most of these technologies use unlicensed sub-GHz band, which offers robust and reliable communication at low power budgets. The sub-GHz band faces less attenuation, mulitpath fading, and congestion compared to the 2.4GHz. These technologies often employ robust modulation and spread spectrum techniques to achieve reliable, low-power, and interference resistant communication.

Depending on the area of the structure, either short-range or LPWAN technologies can be employed in the durability monitoring IoT systems. In fact, LPWANs are a more natural choice for IoT based monitoring of RC structures because it can cover large area of the structures easily without the need for relay nodes. They are also aesthetically preferable as the number of nodes will be fewer compared to short-range ones. Most of these technologies achieve 10 years of battery lifetime, this is beneficial as it decreases the required number of battery changes throughout the service life time of the structures. Some of the important features of the most popular LPWAN technologies are listed in Table 2.

Table 2. Features of selected LPWAN technologies.

Features	NB-IoT	LoRaWAN	Sigfox
Band	Licensed sub-GHz	Unlicensed sub-GHz	Unlicensed sub-GHz
Max Range (km)	15	15	10
Peak data rate (kbps)	250(UL), 170 (DL)	27	1
Security	Yes	Yes	Yes
Link budget (dB)	164	164	N/A
Battery lifetime (Years)	10	10	5

4. Intelligent data analysis for concrete durability assessment

Adoption of intelligent data analysis technique in various science and engineering disciplines for capturing complex interrelationships among data pairs of input and output, which are nonlinear, unknown or complex to formulate is becoming a common practice. The penetration of CO_2 and chloride ions into concrete involves a complex physical and chemical process that combines various transport mechanisms. The penetration are also controlled by other several factors, including concrete ingredient material properties, mix proportion of ingredients, curing conditions, and the macro- and micro-environment to which the concrete structure is exposed. Developing mathematical models that describe the penetration of the aggressive substances (CO_2 and chloride) into concrete, which take into account the influence of all the controlling parameters, is a challenging task. The advancement of miniaturized sensing devices and IoT technologies make it possible to collect continuous in-service data of various parameters that controls the penetration of CO_2 and chloride ions into the concrete pores. By applying intelligent data analysis technique on the measured long-term data, it is possible to learn the complex interrelation among prominent parameters that controls the penetration of the aggressive substances and construct a prediction model (that predict the time to onset corrosion of reinforcement steel) without assuming a predetermined equation as a model. With the availability of more and more data, the accuracy of prediction improves as it can capture the concrete microstructure changes caused by time-dependent chemical processes of the cement paste and its interaction with the environment. In addition, useful knowledge can be discovered from the data by exploiting intelligent data analysis techniques.

Though employing intelligent data analysis technique is becoming popular in several fields of engineering, its use in durability and service-life assessment of concrete structures is limited. Indeed, in the past few years, there are few attempts on application of machine learning for concrete durability assessments [29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40] using mainly historical data gathered from experimental field and laboratory tests but not from in-service monitoring systems. The majority of these works were based on short-term tests (few data size) and failed to include some of the important parameters that controls the penetration of carbon dioxide and chloride ions into the concrete. These works are listed in Table 3. As can be seen from Table 3, there is no model that predict the chloride ions concentration but the model were applied to characterize the chloride permeability of the concrete.

Table 3. Machine learning based models applied to characterize carbonation depth and chloride ions penetration in concrete.

Work	Problem type	Learning algorithm	Exposure environment	Number of parameters
[29]	Carbonation depth	Neural network	Field	6
[30]	Carbonation depth	Neural network	Lab	5
[31]	Carbonation depth	Adaptive neuro-fuzzy inference system	Field	6
[32]	Carbonation depth	Neural network	Lab	3
[33]	Carbonation depth	Decision tree	Lab	15
[34]	Carbonation depth	Multiple algorithms †	Field	25
[35]	Permeability	Neural network	Lab	5
[36]	Permeability	Neural network	Lab	6
[37]	Permeability	Support vector regression	Lab	7
[38]	Permeability	Multiple algorithms‡	Lab	4
[39]	Permeability	Neural network	Field and lab	6
[40]	Knowledge discovery*	Bagged decision tree	Field	32

† Neural network, decision tree, bagged decision tree and boosted decision tree.
‡ Neural network and adaptive neuro-fuzzy inference system.
* Determining the influential parameters controlling chloride ions penetration.

5. Data-driven smart RC structures

Recently, smart environments including smart infrastructure based on IoTs and intelligent data analysis techniques have gained attention from both scientific communities and industries with the aim of solving societal problems. But so far, the main focus in case of smart infrastructure is on structural responses due to load. Durability of concrete structures is not only affected by load but also by corrosion of reinforcement steel, which is caused by penetration of aggressive substances into the concrete pores. The IoT based monitoring system proposed above is one-step towards realizing data-driven durability assessment of concrete structures.

With the advancement of sensing technology, the availability of miniaturized, stable and inexpensive sensors for monitoring durability of concrete structures may increase over the next few years. These sensors can be deployed in new and existing RC structures to monitor corrosion causing factors, even in locations where performing routine inspection is challenging. The monitored data will be communicated to remote user using appropriate wireless communication technologies. The collected data will be analyzed using intelligent data analysis techniques in order to autonomously assess the condition of the structures remotely. Hence, the implementation of IoT based system and advanced data analysis methods will form a primary component in the inspection, assessment and management of future RC structures. Ultimately, realizing data-driven smart RC structures.

The conceptual architecture of the envisioned data-driven smart RC structure is shown in Figure 1. Various types of sensors that are deployed in the structure will continuously measure parameters that cause or accelerate corrosion of reinforcement bar and/or other deterioration mechanisms. Measuring such parameters continuously using sensors will provide more reliable data compared to performing periodic sample testing. This approach also leads to cost savings in the long run, taking into an account the labor cost, the users cost, and their safety. The measured data will be sent to cloud storage through gateways. Realistic condition assessment of the structures can be performed autonomously using sophisticated data analysis on the data stored in the cloud and deliver the results to the facility managers, infrastructure owners and other stockholders. The accessibility of short- and long-term data with spatial and temporal resolution from the monitoring system is a critical underlying necessity for efficient durability assessment of RC structures and detection of deterioration at an early stage. This enables the stakeholders to perform condition-based maintenance measures in time, which in turn mitigates maintenance related costs considerably.

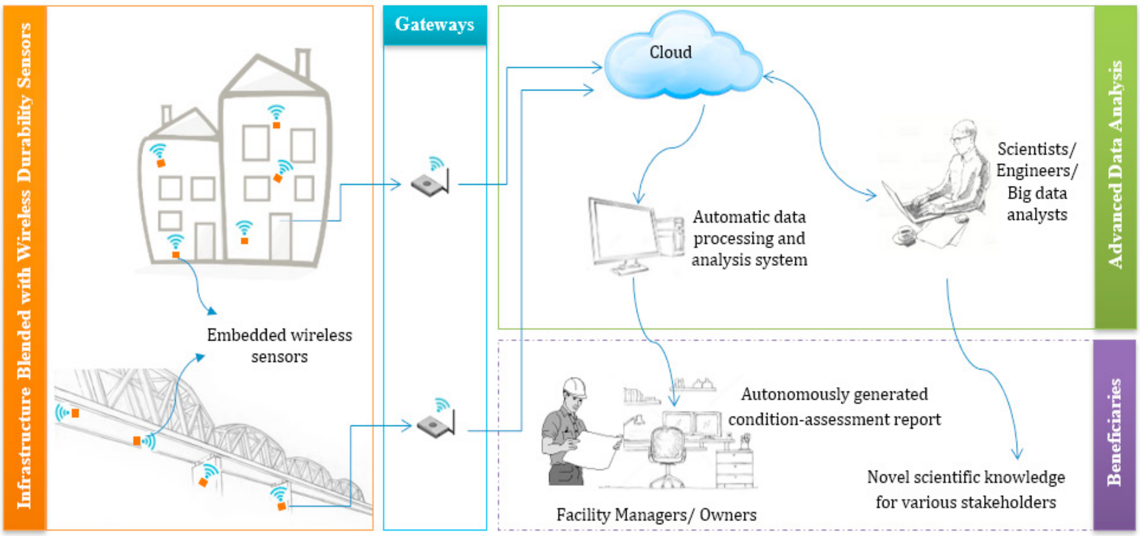

Fig. 1. Architecture of data-driven smart RC structure.

In the proposed architecture, data of several parameters can be shared to other parties, such as data scientists, material scientists, and concrete researchers. Using the data, they can contribute to a better scientific comprehension regarding the complex corrosion, other and combined deterioration mechanisms. Using the conventional approach, measuring the influence of the combined degradation mechanisms in laboratory and translating the results to an actual structure is impractical. Traditionally, corrosion related durability assessment is carried out by evaluating carbonation and chloride ions penetration separately. In reality, these two deterioration mechanisms along with others affect the concrete performance simultaneously. The synergic effect is faster and more severe than the effect of their single action. The proposed data-driven smart RC structure will have the ability to learn the synergistic effect of the degradation mechanisms by utilizing the collected long-term data and intelligent data analysis, enabling discovery of new knowledge. The discovered knowledge will assist scientists and practitioners to devise optimal solutions that improve the durability of the concrete structure as well as to establish proactive maintenance plan.

6. Conclusions

Conceptual framework for autonomous in-service durability monitoring and assessment of RC structures is formulated in this work. The conventional durability assessment results are unreliable due to the limitations in the employed empirical models. It also involves laboratory tests of samples taken destructively from structures, which is time consuming, labor intensive and expensive. The proposed conceptual framework tackles the limitations of the conventional methods by exploiting IoT and advancement in intelligent data analysis techniques. Through the deployment of IoT system in the structure, continuous monitoring and long-term data collection can be ensured. By applying intelligent data analysis technique on the collected data, complex nonlinear interaction of corrosion controlling parameters can be captured, resulting in reliable assessment and discovery of new knowledge. This facilitates timely formulation of appropriate measures for extending the service life of the structure. All these leads to cost-effective management of the RC structures. Moreover, the discovered knowledge will assist material scientists to innovate deterioration resistant concrete mix.

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