Research Article

Self-Powered Wireless Sensor Network for Automated Corrosion Prediction of Steel Reinforcement

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Corrosion is one of the key issues that affect the service life and hinders wide application of steel reinforcement. Moreover, corrosion is a long-term process and not visible for embedded reinforcement. Thus, this research aims at developing a self-powered smart sensor system with integrated innovative prediction module for forecasting corrosion process of embedded steel reinforcement. Vibration-based energy harvester is used to harvest energy for continuous corrosion data collection. Spatial interpolation module was developed to interpolate corrosion data at unmonitored locations. Dynamic prediction module is used to predict the long-term corrosion based on collected data. Utilizing this new sensor network, the corrosion process can be automated predicted and appropriate mitigation actions will be recommended accordingly.

1. Introduction

Corrosion is a deterioration process that would alternate the properties of the material because of a reaction with its environment. Similar to other natural hazards and environmental attacks, corrosion can cause dangerous and expensive damage to different objects from automobiles to pipelines, bridges, and other essential infrastructure systems. Furthermore, the aging infrastructure is one of the most serious problems faced by our society today and corrosion is one of the most severe environmental attacks that affects the service life and functionality of aging infrastructure.

The corrosion of embedded steel reinforcement is one of the principal causes of deterioration of reinforced concrete. It is presumed that when the embedded steel is protected from air by a thick cover of a low permeability concrete, the corrosion problem of steel would not arise. But in reality, this may not be entirely true since many properly built reinforced and prestressed concrete structures show premature deterioration due to steel corrosion. Rebar corrosion is one of the major forms of environmental attack to reinforced concrete,

which may lead to reduction in strength, serviceability, and aesthetics of the structure, as well as affect the application of reinforcement. The corrosion of embedded steel reinforcement will greatly affect the performance, functionality, and serviceability of the structure.

The damage to concrete resulting from the corrosion of embedded steel is visible in the form of expansion, cracking, and eventual spalling of the cover [1, 2]. Besides the loss of cover, a reinforced concrete member suffers structural damage due to loss of bond between steel and concrete and loss of rebar cross-sectional area and its functionality.

Because the corrosion occurs on the embedded reinforcement, the detection of corrosion can be extremely difficult. At early ages, coring sample was the only method to detect the corrosion. However, the coring would only indicate the corrosion condition at the coring location but would not reveal the true condition of structure as a whole. Therefore, corrosion detection technologies were developed including chain drag method (ASTM D4580-12), electrochemical half-cell potential (HCP), Tafel extrapolation technique (TP), linear polarization resistance (LPR) [3–5], macrocell

current (MC) [6], radio-frequency identification (RFID), and sacrificial sensors (SS).

Over the past decades, number of researches have been performed to develop efficient monitoring methods and techniques. Electrochemical methods were investigated and examined at early stage of corrosion monitoring research [7–9]. Later, Baronio et al. [10] performed steel corrosion monitoring based on potential measurements. El-Mahdy et al. [11] conducted electrochemical corrosion monitoring under cyclic wet-dry conditions. Elsener [12] studied the microcell corrosion process of steel in concrete. Montemor et al. [13] presented an overview of chloride-induced corrosion process and monitoring techniques. Moreover, various techniques including galvanostatic pulse technique [14, 15], acoustic emission method [16–18], electrochemical impedance spectroscopy (EIS) [19, 20], and electrochemical noise analysis (ENA) method [19] were developed. Various types of sensors and reference electrodes were developed for corrosion monitoring [21–28]. Automatic system [29], remote corrosion monitoring system [30], 3-D monitoring system [31], and multielectrode system [32] were also developed recently. Performance of different corrosion monitoring techniques were reviewed, compared, and assessed [33–35]. In addition, some of the researches focused on evaluating/ modeling of chloride ingress in concrete based on laboratory and field measured data [36–39].

Initiation time of steel reinforcement corrosion is another important parameter to predict and understand corrosion mechanism of steel reinforcement. Daigle et al. [36] proposed a formula to predict the time of corrosion initiation compose parameters of concrete cover, chloride threshold, and chloride concentration. There are many factors affecting the corrosion rate including temperature, oxygen supply, relative humidity, chloride concentration, alkalinity, resistivity, galvanic interaction, and rust layer formation. There are three main approaches that developed over the years to estimate the corrosion rate [40]: (1) models based on electrochemistry, (2) models related to a diffusion-limited access of oxygen, and (3) models in the form of empirical relations.

Besides corrosion detection, corrosion prediction is also very important in mitigating corrosion damage and associated with deterioration. Over the years, several corrosion prediction methods have been developed by the researchers. Among these prediction methods, some of them focus on the prediction of corrosion rate while other methods focus on prediction of service life of reinforced concrete. While prediction of service life of reinforced concrete is important, corrosion rate or section losses of reinforcement would be a more appropriate parameter to evaluate the performance of the reinforcement in resisting corrosion. As summarized in Figure 1, there are four types of approaches for prediction of corrosion rate [40]: (1) physics-based models, (2) empirical models, (3) statistical prediction models based on various statistical techniques, and (4) heuristic data model.

For physics-based models, there are several approaches that can be used to model the reinforcement corrosion based on electrochemistry, diffusion-limited access of oxygen, and volume-discretization method. The physics-based model developed based on electrochemistry is the most

FIGURE 1: Corrosion prediction method.

common approach. Many researches have been performed to develop a complex corrosion model based on electrochemical principles and Butler-Volmer kinetics [40–43]. Advanced data filtering method and computer programs were also developed in recent years [44, 45]. However, a great amount of details are required for the utilization of these models. Thus, it is impractical for practicing engineers to apply them for the prediction of corrosion [40]. Physics-based models can also be developed based on diffusion-limited access of oxygen. It is known that the access of O_2 at the steel surface in the cathodic zone of rebars is directly related to the corrosion reaction rate. Kobayashi and Shuttoh [46] found that the moisture content of concrete greatly affects the O_2 diffusion efficient. Sudjono and Seki [47] concluded that the coefficient of O_2 diffusion decreases near linearly when the water content increased from 0 to 80%. Boundary element method/boundary integral equation (BEM/BIE) is another physics-based method. BEM/BIE uses Faraday's law for boundary motion to surface flux and uses polarization curves to fit boundary values into the integral equation. One advantage of BEM/BIE is it can incorporate other physical phenomena that impacts corrosion such as stress and impressed current cathodic protection into calculation. On the other hand, BEM/BIE needs detailed polarization curves which is site-specific to each specimen, electrolytic environment, stress, time, and other factors thus is not very practical to apply.

Corrosion prediction models can also be developed based on empirical relations. Siemes et al. [48] proposed a typical empirical model $V_{\text{corr}} = m_o/\gamma \prod F_i$, where V_{corr} is the corrosion rate, m_o is the factor given by the corrosion rate versus electrical resistivity, γ is the electrical resistivity of the concrete, and F_i is the factor influencing the local corrosion rate including chloride corrosion rate factor, galvanic effect factor, oxygen availability factor, and the oxide (rust)

factor. There are several other empirical models that have been developed based on limited data from experimental studies [49, 50]. However, these empirical models are developed based on limited experimental data and do not reflect the basic electrochemical reactions as well as the true nature of the corrosion process thus cannot be used for other cases without proper validation.

Since the reinforcement corrosion depends on many random variables such as temperature, ohmic resistance, chloride content, and exposure time, the corrosion can be predicted using statistical models. Various statistical techniques can be used including Weibull analysis, Monte Carlo simulation, Bayesian networks, Markov chains, and neural networks. However, the prediction needs to be validated and updated based on actual experimental data to ensure the accuracy of prediction. Heuristic data model is another analytical method for corrosion prediction. Heuristic models combine information from design rules, engineering lessons, and observations, and it provides another approach to predict the future corrosion trend of steel reinforcement. Recently, deep learning and machine learning methods also showed promising results in damage detection and prediction [51, 52].

Overall, these corrosion detection and monitoring techniques enable the engineers to detect and monitor the corrosion process of embedded steel reinforcement. However, the key issues related to long-term power supply, data transmission, and long-term reliability need to be addressed.

2. Critical Issues Related to Corrosion Detection and Prediction

Although there are many ways to detect corrosion and predict the corrosion rate, there are some critical issues that hinder the application of these methods in the industry level. These critical issues are as follows:

(1) Local to spatial:

all the previous researches are focused on detection of corrosion at various locations but did not provide a solution on interpolation of corrosion in a spatial scale, which is crucial when evaluating the overall global corrosion condition.

(2) Integration of detection and prediction:

the link between corrosion detection and prediction is missing. To be able to fully utilize the data collected from corrosion detection and take the mitigation action prior to severe corrosion, the corrosion detection and prediction should be integrated as one product.

(3) Data collection, transmission, and storage:

most of the corrosion detection techniques require power supply and wired connection, which greatly limited the broad application in the industrial level. With innovated wireless and energy harvesting

technology, a wireless, battery-less sensor network is desired.

(4) Static versus dynamic self-updating:

the current corrosion prediction methods are static methods that did not consider the variation of environmental conditions and structural conditions over time.

(5) Manual versus automated:

due to lack of linkage between detection data and prediction, manual inputs and modeling are required for corrosion prediction and this procedure needs to be improved; therefore, automated prediction can be performed.

Besides these general critical issues, there are many other unsolved issues related to corrosion detection and prediction. Figure 2 presents the comparison of current and proposed corrosion prediction method.

3. Proposed Wireless Sensor Network

In order to develop a corrosion monitoring and prediction system that integrates monitoring, data processing, spatial interpolation, prediction, alert triggering, and decision making, the research framework depicted in Figure 3 is adopted. It contains various modules for different functions. Experimental and analytical studies is closely integrated to achieve automated corrosion prediction for embedded steel reinforcement.

3.1. Corrosion Monitoring and Data Collection Module. Due to the critical issues presented in previous sections, there is an urgent need to develop a reliable, durable, self-powered, and wireless sensor network for long-term corrosion monitoring. A corrosion monitoring sensors that coupled with energy harvesting modules allow long-term monitoring of steel rebar corrosion with minimum maintenance requirements. It is well documented that the power requirement of SHM systems is especially a problem for structures in remote areas. It is even more critical for corrosion monitoring since corrosion of steel reinforcement takes tens of years to develop thus normal battery power cannot last that long period of time. Therefore, a self-powered wireless corrosion sensor with energy harvesting feature has been developed in this research.

The main energy harvesting sources in structures are solar, thermal gradient, wind and aeroelastic vibration, and ambient mechanical vibration. There are several emerging concepts in harvesting energy from concrete structures. Yu et al. [53] used the corrosion energy to produce electrical energy for wireless sensors. Ye and Soga [54] developed a methodology that converts water distribution system movement to electrical energy. García and Partl [55] proposed a method to harvest energy using parallel air conduits placed inside the asphalt that generates airflow to trigger wind turbines. In general, the selection of proper energy sources depends on the power requirement, the

FIGURE 2: Comparison of current and proposed corrosion prediction methods.

installation location, and available ambient energy. As shown in Table 1, the power density that generates from different sources varies.

Currently, most of energy-harvesting devices (with the exception of solar panels) are in prototype phase and only have been tested under controlled laboratory conditions. Thus, in this research, a self-powered wireless sensor network with energy harvesting capability that can be used in harsh field conditions is developed.

Although there are many sources that can be used to harvest energy, considering the limited availability and lack of consistency for solar radiation and thermal gradient, ambient vibration is a good source of ambient energy that can be used to convert to usable electrical energy due to the fact that the majority of steel reinforced concrete structure subjected to dynamic loading including wind, seismic, machinery, and vehicular load. There are several types of vibration-based energy harvesters: piezoelectric vibration energy harvesters (PE-VEH), electrostatic vibration energy harvester (ES-VEH), and electromagnetic vibration energy harvester (EM-VEH) [57]. Due to usage of initial charging source and requirement of the electronic switch circuit during the operation, ES-VEH is not a good option in comparison with PE-VEH and EM-VEH. Comparing PE-VEH and EM-VEH, PE-VEH is used in this research due to its relatively better power density/acceleration performance.

As shown in Figure 4, for piezoelectric vibration energy harvester, a piezoelectric material is deposited on the surface of the steel reinforcement. When the reinforcement vibrates or deforms, the piezoelectric material is subjected to deformation as well. Due to the nature of piezoelectric material, the deformation will induce voltage. Figure 4(b) shows a

prototype self-powered wireless corrosion sensor that has been installed in reinforced concrete deck for long-term monitoring. The total potential energy can be estimated using (1) developed by Rhimi and Lajnef [58]

$$U = \frac{1}{2} \int_{V_s} S^T T dV_s + \frac{1}{2} \int_{V_p} S^T T dV_p + \frac{1}{2} \int_{V_p} E^T D dV_p + \frac{1}{2} \int_L P \left(\frac{\partial u}{\partial x} \right)^2 dx, \quad (1)$$

where S is strain, T is stress, E is electric field, D is electric displacement, and V is the volume of piezoelectric material.

The battery-free corrosion sensors coupled with wireless modules including gateway and base station enables continuous real-time data collection. Since communication of data consumes significant amount of energy. Thus, data transmission and routing are carefully designed to minimize the consumption of power. Data compression method is applied to reduce the data size. There are two compression algorithms: lossless and lossy compression. Because the lossless compression guarantees the integrity of data without distortion, lossless compression algorithm is used in this study. Comparing to the existing corrosion detection/monitoring system, the key features of this approach are (1) the use of energy harvesting instead of battery powered. Battery-powered sensors impose great limitation on the length of possible service life of the sensor since the sensor will be embedded with the steel reinforcement. Especially for the monitoring of a process as corrosion that takes long time to develop, the continuous power supply over tens of years is essential; another key feature is (2) the application of wireless technology. Taking advantage of state-of-the-art wireless technology to establish

FIGURE 3: Research framework.

TABLE 1: Characteristics of various energy-harvesting techniques [56].

	Conditions	Power density	Area or volume	Energy/day
Vibration	1 m/s ²	100 μ W/cm ³	1 cm ³	8.64 J
Solar	Outdoors	7500 μ W/cm ²	1 cm ²	324 J (assuming light is available for 50% of the time)
Solar	Indoors	100 μ W/cm ²	1 cm ²	4.32 J (assuming light is available for 50% of the time)
Thermal	$\Delta T = 5^\circ\text{C}$	60 μ W/cm ²	1 cm ²	2.59 J (assuming light is available for 50% of the time)

a wireless sensor network to replace the traditional wired sensor network is a significant advancing.

3.2. Spatial Interpolation Module. Because only limited number of sensors can be instrumented in the field, in order to obtain the corrosion condition from the structure level, a spatial interpolation algorithm is needed. As illustrated in Figure 5, a series of sensors will be installed at selected locations (green and purple dots). Data from some of the sensors (green dots) will be used as input for spatial interpolation model while data from other sensors (purple dots) will be used to validate the model. Various input/validation sensor combinations will be examined to identify the most accurate

interpolation model to predict the corrosion at unknown locations (red dots).

The spatial correlation of different locations will be examined by spatial statistical simulation with semivariogram. Semivariogram is a statistical tool that measures regionalized spatial variable $x(\mathbf{u}_\alpha)$, where $\mathbf{u}_\alpha$ is the coordinate vector at each of the observation points in a two or three dimensional space [59]. The empirical semivariogram $\gamma(\mathbf{h})$ can be calculated using

$$\gamma(\mathbf{h}) = \frac{1}{2N(\mathbf{h})} \sum_{\alpha=1}^{N(\mathbf{h})} [x(\mathbf{u}_\alpha) - x(\mathbf{u}_\alpha + \mathbf{h})]^2, \quad (2)$$

FIGURE 4: (a) Scheme for wireless corrosion sensor and (b) prototype.

FIGURE 5: Illustration of spatial interpolation.

where $\gamma(\mathbf{h})$ is the estimated value of the semivariance for vector $\mathbf{h}$; $N(\mathbf{h})$ is the number of experimental pairs separated by vector $\mathbf{h}$; and $x(\mathbf{u}_\alpha)$ is a spatial variable.

Various statistical models including spherical, exponential, Gaussian, linear, and power models will be used to fit the experimental semivariograms. The model that produces the least error will be used for further analysis.

There are several spatial interpolation methods available including arithmetic mean method, the nearest neighbor method, distance weighted method, and polynomial interpolation method. Because kriging method considers the spatial structure properties and spatial correlations, kriging will be used for spatial interpolation modeling. Using the structural properties of semivariogram and the initial set of experimental data values, kriging is capable of making optimal, accurate estimates of regionalized variable at unknown locations. Spatial interpolated prediction $Z(x_0)$ from ordinary kriging (OK) is defined as follows:

$$Z(x_0) = \sum_{\alpha=1}^n \lambda_{\alpha}^{\text{ok}} Z(x_{\alpha}), \quad (3)$$

where $\lambda_{\alpha}^{\text{ok}}$ is the OK weights and the summation should be equal to 1. Thus, the key to an appropriate prediction is selecting appropriate weights for respective available observations. The criteria of selection are to minimize the kriging variance $\sigma_{\text{ok}}^2(x_0) = -\gamma(0) - \sum_{\alpha=1}^n \sum_{\beta=1}^n \lambda_{\alpha}^{\text{ok}} \lambda_{\beta}^{\text{ok}} \gamma(x_{\alpha} - x_{\beta}) + 2 \sum_{\alpha=1}^n \lambda_{\alpha}^{\text{ok}} \gamma(x_{\alpha} - x_0)$, where γ is the estimated value of the semivariance. This minimization process can be done using Lagrange multipliers.

3.3. Corrosion Prediction Module. Corrosion prediction can be mystical since the corrosion of steel reinforcement is a long process and it is invisible and even is not noticeable unless the concrete cover got peeled off. However, on the other hand, accurate prediction of corrosion is very important and extremely helpful for the owner to develop a more efficient maintenance plan and take mitigation measures in advance. As presented in previous sections, there are several corrosion prediction methods that have been developed. However, there are some critical issues that limited the further and wide application of these prediction methods. Furthermore, since there is no direct linkage between data collection and prediction, tremendous effects are needed to perform the corrosion prediction and there is no practical way to validate the accuracy of the prediction. Therefore, the authors developed a corrosion prediction algorithm that is automated, self-updating, and incorporated with corrosion monitoring and data collection.

For time-related variation or development, there are two quantitative forecasting methods that can be used: (1) causal models and (2) time series models. Comparing to causal models, time series models take trend, cyclical, seasonal, and irregular events into consideration and its progressive feature provides a unique updating algorithm which greatly improves the accuracy of prediction. Thus, automatic time series forecasting is used for corrosion prediction in this study. Many predictive models have been investigated including linear, quadratic, exponential, autoregressive, and state-space models. For automatic time series forecasting algorithm, if the observed corrosion rate is denoted by y_1 ,

FIGURE 6: Specimens prepared for field exposure [62].

$y_2, \dots, y_n$. A forecast denoted as $\hat{y}_{t+h|t}$ at h periods ahead can be estimated using $\hat{y}_{t+h|t} = l_t + b_t h + s_{t-m} + h_m^+$, where m is the length of seasonality, l_t represents the level of the series, b_t represents the growth, s_t is the seasonal component, and $h_m^+ = [(h-1) \bmod m] + 1$. l_t , b_t , and s_t can be calculated using [60]

$$\begin{aligned} l_t &= \alpha(y_t - s_{t-m}) + (1 - \alpha)(l_{t-1} + b_{t-1}), \\ b_t &= \beta^*(l_t - l_{t-1}) + (1 - \beta^*)b_{t-1}, \\ s_t &= \gamma(y_t - l_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m}, \end{aligned} \quad (4)$$

where the initial state of each parameter l_0 , b_0 , and $s_{1-m}, \dots, s_0$ and the smoothing parameters α , β^* , and γ can be estimated from experimental data.

To evaluate the accuracy of the predictive models, measures such as mean squared error (MSE) can be applied. However, it might difficult to draw reliable conclusions because of too few out-of-sample errors. Thus, a penalized likelihood method such as Akaike's information criterion (AIC) that based on in-sample fit has been proven to be a better approach and is used in this study to evaluate the accuracy of the predictive models. The formulas for AIC method are presented in the following equations:

$$\begin{aligned} \text{AIC} &= L^*(\hat{\theta}, \hat{x}_0) + 2q, \\ L^*(\theta, x_0) &= n \log \left(\sum_{t=1}^n \varepsilon_t^2 \right) + 2 \sum_{t=1}^n \log |r(x_{t-1})|, \end{aligned} \quad (5)$$

where $L^*(\hat{\theta}, \hat{x}_0)$ is the maximum likelihood function, $\theta = (\alpha, \beta, \gamma, \phi)'$, $x_0 = (l_0, b_0, s_0, s_{-1}, \dots, s_{-m+1})'$, n is the number of observations, $\varepsilon_t = y_t - \mu_t$ is the one-step forecast error at time t . q is the number of parameters in θ plus the number of free states in x_0 . The model that produce the least AIC will be selected for corrosion prediction.

The framework for automatic prediction algorithm can be summarized as (1) for each set of experimental data, apply all models and optimize the smoothing parameters and initial state variables for each model; (2) calculate AIC and select the best model based on AIC; (3) produce prediction at various time points using the best model with optimized parameters; (4) and continuously update the prediction based on newly collected experimental data.

4. Proof of Concept

Due to the lack of reliable sensors that can be used for long-term corrosion monitoring, very limited experimental study

has been performed on long-term corrosion performance of embedded reinforcement especially under field conditions. Flint and Cox [61] investigated the resistance of stainless steel partly embedded in concrete to corrosion by seawater under lab conditions. However, no continuous data was collected on corrosion of steel. Gartner et al. [62] evaluated the long-term corrosion performance of embedded reinforcement based on monitoring data for more than five years under various conditions. Multielectrodes coupled with stainless or carbon steel electrical resistance (ER) probes were embedded in reinforced concrete columns which placed vertically in sea water under a bridge. As shown in Figure 6, corrosion was monitored at five different exposure zones: the in-water zone, the zone below the surface, the tidal zone, the splash zone, and the dry zone. The monitoring lasted for five years with measurements being taken several times a year. In order to validate the prediction algorithm that developed in this study, the long-term corrosion monitoring data collected by Gartner et al. [62] was used.

Figures 7 and 8 present the comparison between experimental data collected by Gartner et al. [62] and predicted values using the algorithm presented in this research for tidal zone and in-water zone, respectively. As shown in the comparison, using the prediction algorithm presented in this research, the prediction accurately represented the trends of corrosion at different locations for a period of 5 years. The prediction captured seasonal variation and the trends of peak values. Abnormal drop was observed in measured current at tidal zone around 1100 days (Figure 7). Since the overall trend is upward, it is suspected the drop is because of improper measurement or reading. Furthermore, due to the self-updating nature of prediction algorithm, the prediction will become even more accurate when more data is available.

5. Conclusions

Although the corrosion of embedded steel reinforcement is one of the major attacks that affects the serviceability and service life of concrete infrastructures, there is no existing technology that could provide reliable long-term monitoring data due to the limitation on battery life and data communication, let alone future predication. In this paper, an automated corrosion prediction framework was developed for embedded steel reinforcement. With a self-powered wireless sensor network incorporated with spatial interpolation module and corrosion prediction module, the long-term corrosion of embedded reinforcement can be monitored and predicted efficiently and accurately. Prototype sensors were developed and installed in a reinforced concrete bridge deck.

FIGURE 7: Comparison between experimental data and prediction (tidal zone).

FIGURE 8: Comparison between experimental data and prediction (in-water zone).

In addition, the prediction algorithm was compared and examined using five years of monitoring data and the prediction accurately represented the trends of corrosion at different locations.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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