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Change point detection in corrosion health monitoring using statistical techniques

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With the development of more comprehensive strategies for on-line monitoring and the developments in smart sensor technology and digital data acquisition, there is a need to develop change point detection algorithms which can be used on-line for automated diagnosis of structural health. This is especially required in the case of bridge stocks consisting of large number of bridges which are monitored simultaneously. For structures affected by chloride-induced corrosion of reinforcement, the ability to detect corrosion of reinforcement in its early stages is critical in directing repairs to the most at-risk structures and will help in optimizing the use of limited funds. In this study, the identification of time of corrosion initiation is modeled as a problem of change point detection in online monitored electrochemical current noise data. For change point detection, an algorithm based on maximum likelihood approach is considered. Formulations are made for the determination of window size for the online monitored data points to be considered and the threshold value for the decision function. The usefulness of the algorithm is studied by considering an example problem of identification of time of corrosion initiation in a reinforced concrete bridge girder, in a Monte Carlo simulation framework. The studies presented in this paper are towards realizing sustainable infrastructure considering service life planning and declaration and assessment of sustainability aspects.

KEYWORDS: Reinforced concrete; chloride-induced corrosion; corrosion initiation; change point detection; structural health monitoring.

At present, the design and construction of infrastructural systems is guided by functional performance and conventional financial costing. However, the need to consider the sustainability of the built environment in the infrastructural design decisions is an important issue warranting attention. Sustainability implies that the needs of the present generation are met without wasting, polluting or damaging/destroying the environment and without compromising the ability of the future generations to meet their needs. A sustainable infrastructure should take into consideration the three dimensions of sustainability, namely, social, environmental and economical. According to the concept of sustainability, the entire life cycle of a structure or an infrastructure can be divided into five phases, 'from cradle to grave', including planning, design, construction, operation/maintenance and removal. The concept of sustainability brings to the fore the importance of: (a) life-cycle management, (b) rational scheduling of in-service inspection, (c) repair and rehabilitation, retrofitting, (d) use of energy efficient/non-conventional materials of construction at various stages of life of the structure, and, (e) application of advanced research tools/techniques to ascertain the efficiency of existing structures and/or extend the life of the existing structures.

The ISO standards (ISO 15392, ISO 15686) [1,2] aim to implement the concept of sustainability and to bring consideration of sustainability to an internationally established common ground[3]. These standards are performance-based rather than prescriptive, and embrace the concept of performance-based building (The term building here refers to the activity of building). This concept is based on the clear and unambiguous identification of verifiable performance requirements. The concept of service life planning allows for the consideration of how the performance of the building develops over time. A design option is considered reasonable when it meets or exceeds the performance requirements over time. The methodological context of performance-based building, service life planning, and declaration and assessment of building related sustainability is shown in Fig. 1.

Performance-based building (PBB): Considering performance-based building as a starting point helps in establishing clear and quantitative performance requirements, which can be used to identify a building design that successfully meets the clients' real demands. This requires transforming the user requirements (containing aspects of functionality, quality, comfort, efficiency, etc.) into technical performance requirements. With the identification of perfor-

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mance requirements, the decision process can relate to and restrict itself to these performance requirements.

PBB is, in short, all about handling aspects related to demand of performance requirements to the supply of performance functionality. It may be noted that the supply of performance provided by a building at its design level is only considered here.

In this stage, the demand of performance requirements and the supply of performance by different design alternatives are identified (scenario identification).

Service Life Planning (SLP): Performance of a building usually decreases with time. The concept of SLP allows for the consideration of how the performance of the building develops over time. SLP establishes a rationale for how the long-term performance of a design alternative can be modelled for a specific building design with a defined use pattern and under the exposure to an identified environment.

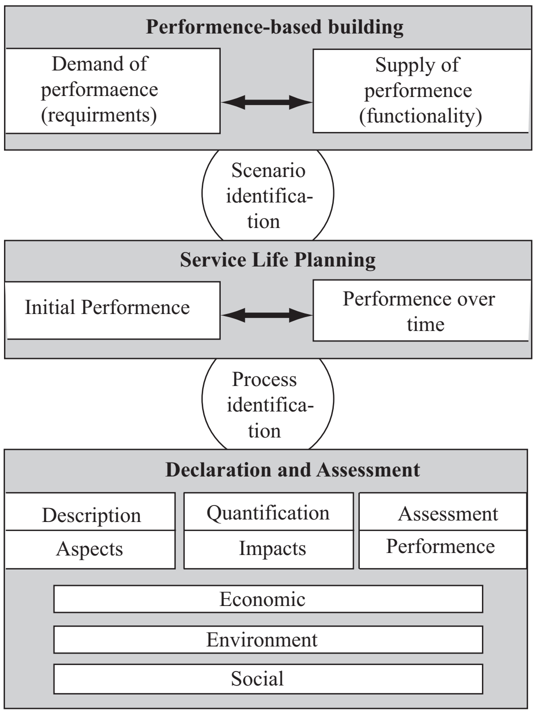


Fig. 1 The sequential relationship of the concepts of performance-based building, service life planning and declaration, and assessment of sustainability aspects of buildings[3].

Modelling the performance over time allows identifying maintenance processes as well as the timing for replacement of components (process identification). Remote health monitoring is an emerging paradigm which needs to be considered at this stage, especially for important infrastructural facilities like bridges.

Declaration and Assessment: The process identification helps in having a more detailed description and a subsequent quantification of all processes and activities taking place during the life cycle of the building (declaration). Using this information, the quantification and assessment of impacts; whether these are economic, environmental, or social, is carried out. Finally, the performances of different design alternatives are assessed, based on which the selection of a particular design alternative is made.

Sustainability of the infrastructure performance can be assessed by performing continuous structural health monitoring. The essence of structural health monitoring can be considered to involve measurement, inspection, and assessment of in-service structures on a continuous basis with minimum labor requirement. Structural health monitoring is a monitoring methodology intended to continuously assess a structural system for identification of damage. Long-term continuous monitoring of major bridges (where long-term designates years-to-decades and desirably the entire life cycle) using permanent monitoring systems, is a very recent concept, enabled by recent advances in sensing, data acquisition, computing, communication, and data and information management[4]. One of the major shortcomings of permanent monitoring systems is the extensive lengths of coaxial wires required for transfer of sensor measurements, which drives up installation and maintenance costs. Straser and Kiremidjian[5] proposed integration of wireless radio with sensor to reduce the cost of structural health monitoring systems. Lynch[6] has extended the functionality of wireless sensors by integrating sophisticated microcontroller with them to enable sensor-based execution of embedded engineering algorithms for data interrogation. Performing data interrogation at the wireless sensor is prudent from an energy standpoint, as wireless radios consume the most power in the wireless sensing unit. Wireless communication of raw time history records would be an inefficient use of limited battery resources. Instead of transmitting raw time history data, the wireless sensing unit is used to first interrogate the data to distil a small number of indicators that would then be wirelessly transmitted. For instance, damage detection algorithms could be used to determine if damage is present and wireless radio is used for transmitting data only if damage was found[7]. The common feature of damage detection is the fact that the problem of interest is the detection of one or several changes in some characteristic properties of the considered system. Thus, many damage detection problems can be stated as the problem of detecting a change in the parameters of a static or dynamic stochastic system. The time instant at which the change of interest occurs is called the change point[8].

From the above discussion, it is noted that there is a need to develop algorithms for change point detection in on-line monitoring data recorded/cached in a central location and analyzed in real-time for automated diagnosis of structural health. In civil structures, the identification of damage before critical failure is of extreme importance. For structures affected by chloride-induced corrosion of reinforcement, the ability to detect corrosion of reinforcement in its early stages is critical in directing repairs to the most at-risk structures and will help in optimizing the use of limited funds. With the development of more comprehensive strategies for on-line monitoring and the developments in smart sensor technology and digital data acquisition[9], there is a need to develop change point detection algorithms which can be used on-line for automated diagnosis of structural health. This is especially required in the case of bridge stocks consisting of large number of bridges which are monitored simultaneously.

From laboratory experimental investigations, it has been noted that electrochemical noise can indicate the current level of corrosion activity of steel in concrete, especially transition from passive state to active corrosion. There is a need to develop automated procedures, which can be used to identify the time of corrosion initiation from the online monitored electrochemical noise data. Towards this, the identification of time of corrosion initiation is modeled as a problem of change point detection in online monitored electrochemical current noise data. For change point detection, an algorithm based on maximum likelihood approach is considered, and the performance of the algorithm is studied in a Monte Carlo simulation framework. The studies presented in this paper are towards the service life planning and declaration and assessment of sustainability aspects for realizing sustainable infrastructure. The details of the studies are given in the following sections.

CORROSION MONITORING USING ELECTROCHEMICAL NOISE TECHNIQUE

Studies by various researchers[10-14] suggested that localized corrosion processes (such as that associated with chloride-induced corrosion of reinforcement in concrete) give particularly strong electrochemical noise response. The type of corrosion is indicated by the coefficient of variation of current noise, ranging from 10^{-3} for general corrosion to 1.0 for localized corrosion[15]. Before initiation of corrosion, the reinforcement in concrete is in the passive state (corrosion currents are negligible, i.e., < 1 mA/m^2) and hence the mean corrosion current can be taken as zero. When depassivation of steel occurs, there is a shift in the mean corrosion current, indicating initiation of active corrosion. Thus, by detecting the shift in the mean corrosion current, time of corrosion initiation can be identified. In this study, identification of time of corrosion initiation is posed as a problem of detection of single change point in on-line monitored electrochemical current noise data.

Electrochemical noise

Electrochemical noise (EN) is a general term for the 'random' fluctuations in current or potential which occurs as an electrochemical process proceeds. EN technique is an emerging technique for monitoring corrosion of reinforcement in concrete[11, 12, 16]. While the corrosion current is related to the rate (kinetics) of the reaction, the electrochemical potential is related to the driving force (thermodynamics) of the reaction. The advantages of EN technique are[14]:

i. Lack of intrusiveness (its application does not involve external perturbation of the corroding system)
ii. Instruments required to make the measurements are reasonably simple, particularly with modern computer-based data acquisition techniques, and,
iii. Localized corrosion processes, which are difficult to monitor with other techniques, tend to give particularly strong EN signals

Measurement of electrochemical noise

Arrangement for measurement of electrochemical noise typically consists of three electrodes arranged as WE-RE-CE or WE-WE-RE or WE-WE-WE, where WE is a working electrode (made of the same type of metal that is being monitored), RE is a reference electrode (which maintains a constant potential in the environment), and CE is a counter electrode (made of a noble material like platinum). The measurement arrangements can be classified as:

i. Potentiostatic (WE-RE-CE) in which constant potential is maintained between WE and RE and the current between WE and CE is monitored and recorded. This arrangement is used in laboratory electrochemical studies under polarized conditions.
ii. Galvanostatic (WE-RE-CE) in which a constant current is passed through WE and CE, and the potential of WE is monitored and recorded against RE, and,
iii. Zero resistance ammeter (ZRA) mode (WE-WE-RE) in which a zero resistance ammeter between two WEs measure the current and a voltmeter between WE and RE measures the potential. This arrangement is used for EN measurements under freely corroding conditions, and is useful for on-line monitoring of corrosion in reinforced concrete structures.

IDENTIFICATION OF TIME OF CORROSION INITIATION AS A CHANGE POINT DETECTION PROBLEM

Consider a reinforced concrete member, wherein the corrosion currents are monitored by recording current flow between two identical, electronically isolated, rebar probes, embedded in concrete, and coupled through a ZRA. At t_i (when depassivation of steel occurs), there is a shift in mean corrosion current, indicating initiation of active corrosion. The actual shift in mean value of corrosion current depends on different factors (viz. humidity content in concrete, temperature, etc.) Andrade et al[17] presented typical ranges for corrosion current for different exposure conditions, based on measurements made on laboratory specimens and on real structures. These ranges of values of corrosion current for different exposures can be further subdivided[18] using typical trend of variation of rate of corrosion with water-cement ratio[19]. Thus, knowing the exposure condition and water-cement ratio used, the range of values of corrosion current that can be expected in the girder after depassivation can be identified, which will give an idea about amplitude of shift in mean corrosion current. Thus, the identification of t_i can be viewed as a problem of identifying the time of shift in mean of the monitored corrosion current data, i.e., a change point detection problem.

The development of algorithms for change point detection in signals is an active area of research with applications in various disciplines[8, 20-24]. The different approaches for solving change point detection problem include maximum likelihood, Bayesian, Bayes-type, nonparametric as well as decision-theoretic procedures[25]. While most of these approaches are based on time-domain analysis, in some cases, it may be required to analyze data in both time and frequency domains. For instance, a step-shift in the mean of the signal is localized in the time domain, whereas a change in variance is more localized in the frequency domain[26]. Thus, if the interest is to detect changes in both mean and variance, the data should be analyzed using a time-frequency approach. Since, in the present study, the interest is in the identification of a step-shift in the mean of the corrosion current data, a time-domain based algorithm is used.

ALGORITHM BASED ON MAXIMUM LIKELIHOOD APPROACH FOR IDENTIFICATION OF TIME OF CORROSION INITIATION

This is one of the oldest and most well known approaches to identify the change detection. The approach is based on the log-likelihood ratio of the observations[8].

It is assumed that the monitored corrosion current data can be represented using a Gaussian white noise (GWN) process. A sample of N observations (N points of the monitored data) is considered, and a decision function is computed to test between the two following hypotheses (H_0 and H_1) about the parameter of interest (mean, μ, in the present study).

$$\begin{aligned} &H_0 : \mu = \mu_0; \qquad \text{no change in occured} \\ &H_1 : \mu = \mu_1; \qquad \text{change has occured} \end{aligned} \tag{1}$$

The change detection is commonly carried out by computing a decision function, S^N, using the observed data, and comparing it with a threshold value Define the decision function, S^N, as:

$$S^N = \sum_{i=1}^{N} S_i \tag{2}$$

where s_i is the log-likelihood ratio for the observations $y_i, i = 1, N$. If $p_Y(y)$ is the probability density function for the observed process, then s_i is defined as:

$$s_i = ln\left(\frac{p_Y(Y_i; \mu = \mu_1)}{p_Y(y_i; \mu = \mu_0)}\right) \tag{3}$$

For the Gaussian process (as considered in the present study), Eq. (3) can be written as:

$$s_i = ln\left(\frac{\frac{1}{\sigma\sqrt{2\pi}}\, e^{-\frac{1}{2}\left(\frac{y-\mu_1}{\sigma}\right)^2}}{\frac{1}{\sigma\sqrt{2\pi}}\, e^{-\frac{1}{2}\left(\frac{y-\mu_2}{\sigma}\right)^2}}\right) \tag{4}$$

where μ_0 is the original mean (equal to zero in the present case) and μ_1 is the changed value of mean of the Gaussian distribution, and σ is the standard deviation of the Gaussian distribution. Simplifying Eq. (4), one get:

$$s_i = \frac{\mu_1 - \mu_0}{\sigma^2}\left(y_i - \frac{\mu_1 + \mu_0}{2}\right) \tag{5}$$

The above equation can be written as (Basseville and Nikiforov, 1993):

$$s_i = \frac{b}{\sigma}\left(y_i - \mu_0 - \frac{A}{2}\right) \tag{6}$$

where

$$A = \mu_1 - \mu_0 \tag{7}$$

is the amplitude of shift and

$$b = \frac{\mu_1 - \mu_0}{\sigma} \tag{8}$$

is the signal-to-noise ratio (since the signal to be detected is the change in mean from μ_0 to μ_1 and σ is the characteristic of the noise in the observations about the mean).

Substituing Eq. (6) in Eq. (2), the decision function becomes:

$$S^N = \frac{b}{\sigma}\sum_{i=1}^{N}\left(y_i - \mu_0 - \frac{A}{2}\right) \tag{9}$$

The stopping rule (decision rule) for the change detection algorithm is given by:

$$d = \begin{cases} 0 \quad if \quad S^N < h; \quad H_0 \quad \text{is chosen} \\ 1 \quad if \quad S^N \geq h; \quad H_0 \quad \text{is chosen} \end{cases} \tag{10}$$

where h is a conveniently chosen threshold. The threshold value can be chosen based on the error probabilities in hypothesis testing. When a decision regarding a hypothesis is made, four possibilities exist and two of them lead to error (Fig. 2).

	accept H_0	accept H_1
H_0 is true	No error	Type I error
H_1 is true	Type II error	No error

Fig. 2 Schematic of decision possibilities in hypothesis testing.

Type I error occurs when there is actually no change in mean but the algorithm detects a change in mean, while Type II error occurs when there is actually a change in mean but the algorithm does not detect the change. The probability of Type I error is called the significance level (α) of the hypothesis test, and the probability of Type II error is called the operating characteristic (β) of the hypothesis test[27]. The complementary probability $(1 - \beta)$ is called the power of the test. In change detection, Type I- and Type II- errors are called false detection and non-detection, respectively. The probability of false detection (P_{FD}) and the probability of non-detection (P_{ND}) are two of the different performance indices used for designing and evaluating change detection algorithms, and these two values should be as low as possible. There is a trade-off between the probability of false detection and the probability of non-detection, and as one is reduced, the other one increases. The probability of false detection need to be kept to a minimum based on economic considerations since a detailed inspection need to be carried out every time the algorithm detects a change. However, in the case of chloride-induced corrosion of reinforcement in reinforced concrete structural members, timely identification of corrosion initiation is important for controlling the damage due to corrosion and for cost-effective maintenance and repair. Therefore, the probability of non-detection should be kept as a minimum, based on economic and social considerations. This can be achieved by suitably choosing the sample size (N) and the threshold (h). A procedure is given in the following section for determining the values of N and h, based on the allowable values of probability of false detection and the probability of non-detection.

Determination of sample size and threshold for the decision function - proposed method

The determination of probability of false detection and the probability of non-detection requires the estimation of the mean and standard deviation (SD) of S^N. The same can be determined as follows.

Since in the present study, $\mu_0 = 0$, the amplitude of shift $A = \mu_1$ (from Eq. (7)). Accordingly, the decision function given by Eq. (9) can be written as:

$$S^N = \frac{b}{\sigma}\sum_{i=1}^{N}\left(y_i - \frac{A}{2}\right) = \frac{b}{\sigma}\left(\sum_{i=1}^{N} y_i - \frac{N\mu_1}{2}\right) \tag{11}$$

Suppose there are r sample points corresponding to the Gaussian process with changed value of mean (μ_1). Then Eq. (11) can be written as:

$$S^N = \frac{b}{\sigma}\left(\sum_{i=1}^{N-r} y_i + \sum_{i=N-r+1}^{N} y_i - \frac{N\mu_1}{2}\right) \tag{12}$$

Since the y_i's are Gaussian, S^N follows a Gaussian distribution. The mean and variance of S^N are given by:

$$\begin{aligned} \langle S^N \rangle &= \frac{b}{\sigma}\left(\sum_{i=1}^{N-r}\langle y_i\rangle + \sum_{i=N-r+1}^{N}\langle y_i\rangle - \frac{N\mu_1}{2}\right) \\ &= \frac{b}{\sigma}\left((N-r)\mu_0 + r\mu_1 - \frac{N\mu_1}{2}\right) \qquad (13) \\ &= \frac{b}{\sigma}\,\mu_1\left(r-\frac{N}{2}\right) \\ &= b^2\left(r-\frac{N}{2}\right) \\ var\left[S^N\right] &= \left(\frac{b}{\sigma}\right)^2\left(\sum_{i=1}^{N-r} var[y_i] + \sum_{i=N-r+1}^{N} var[y_i]\right) \\ &= \left(\frac{b}{\sigma}\right)^2\left((N-r)\sigma^2 + r\sigma^2\right) = b^2 N \qquad (14) \end{aligned}$$

It is noted from these equations [Eqs. (13) and (14)] that the mean and variance of S^N depend upon the signal-to-noise ratio (b) and the sample size (N). If there are no change points, then $r = 0$ and $\langle S^N \rangle = -\frac{b^2 N}{2}$, that is the mean value of the decision function is negative when there are no change points in the data. When all the N data points are with a change in mean, then $r = N$ and $\langle S^N \rangle = \frac{b^2 N}{2}$. This is in agreement with the typical behaviour of the decision function corresponding to a change in the mean of a Gaussian sequence with constant variance[8].

Let S_0^N and S_r^N represent S^N corresponding to the hypotheses H_0 and H_1, respectively. For hypothesis $H_0, r = 0$ and for hypothesis H_1, r can be any value between 1 to N. Therefore, the values of mean and variance of S_0^N and S_r^N can be determined as:

$$\begin{aligned} \langle S_0^N \rangle &= b^2\left(0-\frac{N}{2}\right) = -b^2\frac{N}{2} \\ var[S_o^N] &= b^2 N \qquad (15) \\ \langle S_r^N \rangle &= \sum_{r=1}^{N}\langle S^N\rangle = \sum_{r=1}^{N} b^2\left(r-\frac{N}{2}\right) \\ &= b^2\left(\frac{N(N+1)}{2} - \frac{N^2}{2}\right) = b^2\frac{N}{2} \qquad (16) \\ var[S_r^N] &= \sum_{r=1}^{N} var[S^N] = \sum_{r=1}^{N} b^2 N \\ &= b^2 N^2 \end{aligned}$$

As explained above, false detection occurs when H_1 is chosen (a change is detected) when H_0 is actually true (there is actually no change in mean). This happens when the value of the decision function S_0^N becomes larger than the threshold, h. Thus, the probability of false detection (P_{FD}) is given by:

$$P_{FD} = \alpha = Pr(S_0^N > h) = 1 - Pr(S_0^N \le h) \qquad (17)$$

Since S_0^N follows a Gaussian distribution, Eq. (17) can be written as

$$\alpha = 1 - \Phi\left(\frac{h - \langle S_0^N\rangle}{SD[S_0^N]}\right) \qquad (18)$$

where $\Phi(.)$ represents the cumulative density function of standard normal distribution and $SD[.]$ represents the standard deviation. Substituting for $\langle S_0^N \rangle$ and $SD[S_0^N]$ using Eq. (15) in Eq. (7),

$$\alpha = 1 - \Phi\left(\frac{h + b^2\frac{N}{2}}{b\sqrt{N}}\right) \qquad (19)$$

The non-detection occurs when H_0 is chosen (no change is detected) when H_1 is actually true (there is actually a change in mean). This happens when the value of the decision function, S_r^N, remains within the threshold, h. Thus, the probability of non-detection (P_{ND}) is given by:

$$P_{ND} = \beta = Pr\left(S_r^N \le h\right) \qquad (20)$$

Since S_r^N follows a Gaussian distribution, Eq. (20) can be written as

$$\beta = \Phi\left(\frac{h - \langle S_r^N\rangle}{SD[S_r^N]}\right) \qquad (21)$$

Substituting for $\langle S_r^N \rangle$ and $SD[S_r^N]$ using Eq. (16) in the above equation,

$$\beta = \Phi\left(\frac{h - b^2\frac{N}{2}}{bN}\right) \qquad (22)$$

From Eqs. (19) and (22), it is noted that α and β are functions of both N and h. For the specified values of α and β, Eqs. (19) and (22) can be solved simultaneously to obtain the required values of N and h to be used in change point detection.

The usefulness of the proposed algorithm for identification of corrosion initiation is illustrated through an application.

APPLICATION

A reinforced concrete bridge girder, located in a severe environment (as per the definitions of exposure conditions in IS 456-2000[28] with cross-sectional details as shown in Fig. 3 is considered. For studying the efficiency of the proposed algorithms for change point detection, an ensemble of $y(t)$ is generated which is assumed to represent the electrochemical current noise data obtained from on-line monitoring and stochasticity in time of occurrence of change point event (initiation of chloride-induced corrosion) is taken into consideration. The entire problem has been formulated within the framework of Monte Carlo simulation[29], and is depicted schematically in Fig. 4.

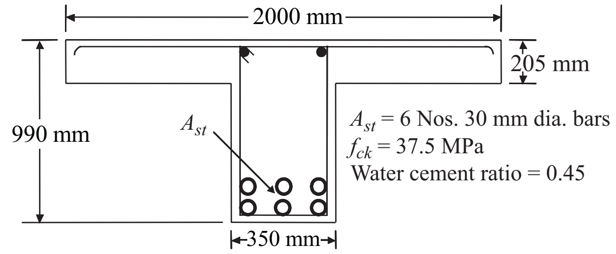
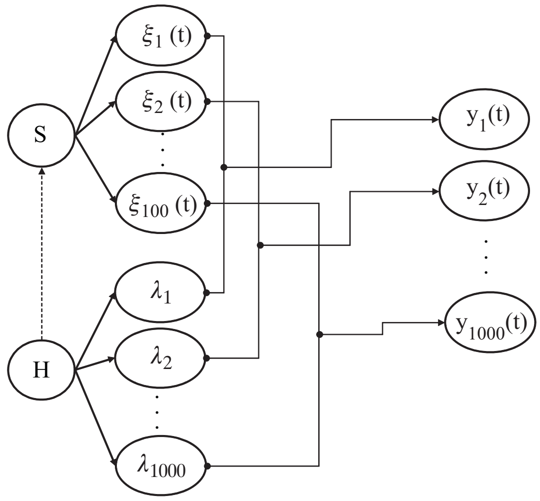


Fig. 3 Cross-sectional details of reinforced concrete bridge girder.



S - System (reinforced concrete structural member)
ξi (t), i = 1,2, …, 1000 – Different realizations of response of system (electrochemical current noise) when there were no active corrosion
H – Initiation of chloride-induced corrosion due to due to ingress of chlorides from environment (hazard)
λ_i, i = 1,2, …, 1000 – Different realizations of time ofcorrosion initiation
y_i (t), i = 1,2, …, 1000 – Different realizations of response of system with the initiation of chloride-induced corrosion at time λ_i

Fig. 4 Schematic representation of problem considered.

Assuming ingress of chlorides into cover concrete as a diffusion process, time-to-corrosion initiation (t_i) can be determined from Fick's second law of diffusion as

$$t_i = \frac{d^2}{4D}\left[erf^{-1}\left(\frac{c_s - c_{cr}}{c_s}\right)\right]^{-2} \tag{23}$$

where d is the clear cover to reinforcement, D is the diffusion coefficient for chlorides in concrete, c_s is the surface chloride concentration and c_{cr} is the critical chloride concentration. To account for variations in workmanship and exposure conditions, d, D, c_s and c_{cr} are treated as random variables. The values of mean and standard deviation of these random variables are given in Table 1. All the random variables are assumed to be statistically uncorrelated with each other. The mean and standard deviation of time-to-corrosion initiation are determined using first order approximation as 14.11 years and 9.42 years, respectively. It is assumed that t_i follows a lognormal distribution[30].

TABLE 1
VALUES OF MEAN AND STANDARD DEVIATION (SD) FOR THE RANDOM VARIABLES CONSIDERED

variable	mean	SD	Remarks
d (mm)	45	2.25	Assumed cov of 0.05
D (cm^2/s)	5×10^{-8}	1×10^{-8}	cov = 0.20 (Balaji Rao et al, 2004)[31]
c_s (% by weight of concrete)	0.25	0.05	cov = 0.20 (Balaji Rao et al, 2004)[31]
c_{cr} (% by weight of concrete)	0.125	0.025	Assumed cov of 0.20

The amplitude of shift in mean corrosion current is taken as $0.15\mu A$, with a standard deviation of $0.05\mu A$, which is consistent with exposure condition considered for the girder. In the present study, simulated electrochemical noise data, representing the monitored corrosion currents, is used. Cottis et al[32]. used a shot noise model to simulate electrochemical noise data. It is assumed that monitored electrochemical noise data can be represented by a GWN process. One thousand realizations of GWN process are generated representing the possible realizations of monitored electrochemical noise for a period of 100 years at an interval of 0.01 years. One thousand lognormal random variables, representing time-to-corrosion initiation, one for each realization of the observed process, are generated. Typical realizations of the observed process (electrochemical noise) without and with shift (corrosion initiation) are shown in Fig. 5.

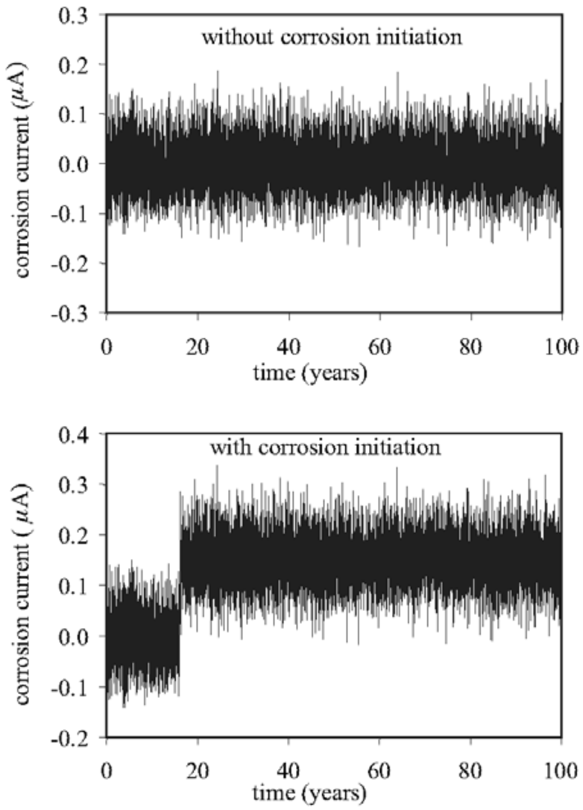


Fig. 5 Typical realizations of the observed process (simulated in the present study) without- and with- shift (time of corrosion initiation = 16.1 years).

RESULTS AND DISCUSSION

For the problem considered, the signal-to-noise ratio (b) is 3. The variation of decision function, S^N, with time for a typical realization of the observed process, for sample size $N = 100$, is shown in Fig. 6. It is noted from this figure that, as expected, the value of S^N is negative in the beginning (when there is no shift), with a magnitude around the mean value of $S_0^N(\langle S_0^N\rangle = -b^2\frac{N}{2} = -450$ using Eq. 15) corresponding to the hypotheses H_0. After the shift has occurred (corrosion has initiated), the value of S^N increases till the number of changed points in the sample becomes N, i.e., $r = N$. After this, the value of S^N is around the mean value $= b^2\frac{N}{2} = 450$ (using Eq. 16), as is noted from Fig. 6.

Considering a 1% level of significance (probability of false alarm = 0.01), the variation of sample size (N) and threshold (h) required for different values of probability of non-detection are shown in Fig. 7.

From Fig. 7, it is noted that as the probability of non-detection decreases, N increases, and h decreases. This suggests that a large value of N should be chosen for minimizing the probability of non-detection. But, as the sample size increases, the delay in detection also increases. This is because one has to wait till the window is completely filled for computing the value of decision function. Thus, an optimal value of probability of non-detection should be selected considering the delay in detection also. The variation in mean and standard deviation of delay in detection for different values of probability of non-detection are shown in Fig. 8.

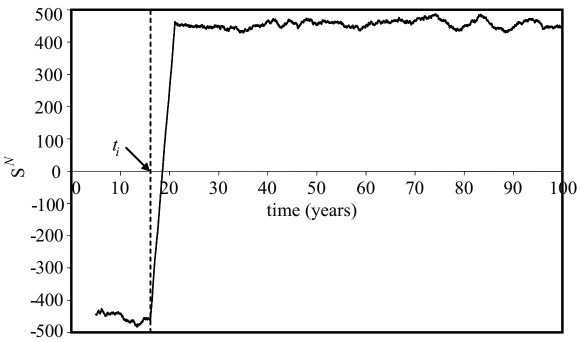


Fig. 6 Variation of decision function with time (N = 100, time of corrosion initiation = 16.4 years).

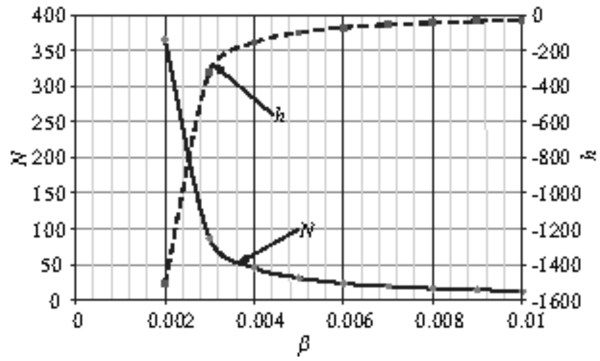


Fig. 7 Variation in sample size and threshold with probability of non-detection (probability of false detection, α = 0.01).

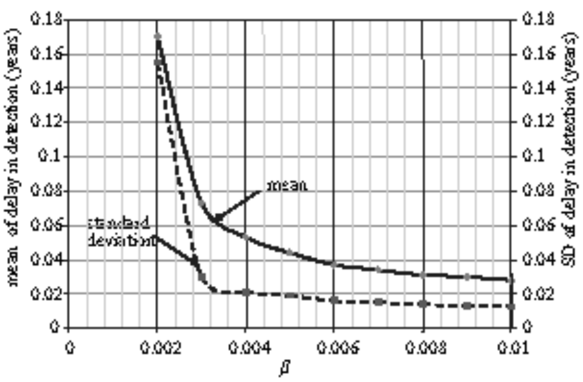


Fig. 8 Variation in statistical properties of delay in detection with probability of non-detection.

From Fig. 8, it is noted as probability of non-detection decreases (accordingly, the sample size N required increases), the mean and standard deviation of delay in detection increases. However, upto a value of 0.0035 of probability of non-detection, the increase in the mean and standard deviation of delay in detection is marginal. If the probability of non-detection is decreased further, there is a sudden increase in the mean and standard deviation of delay in detection. Therefore, the optimal value of probability of non-detection for the problem considered is about 0.0035 (0.35%). The corresponding values of N and h (from Fig. 7) are 59 and -265.5. These values are used in the present study for change point detection. The comparison of actual and predicted values of time of corrosion initiation is shown in Fig. 9, and frequency distributions of the same are shown in Fig. 10. From these figures, it is noted that the predicted times of corrosion initiation are in good agreement with the actual times of corrosion initiation.

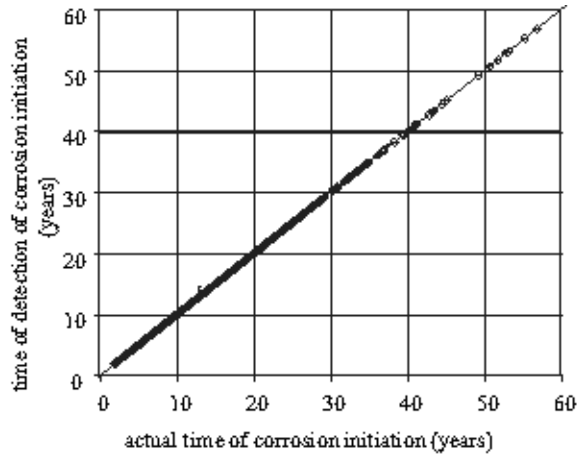


Fig. 9 Comparison of actual and detected times of corrosion initiation.

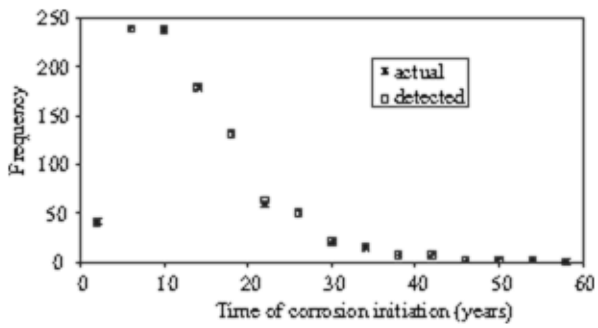


Fig. 10 Frequencies of actual and detected times of corrosion initiation.

The values of mean and standard deviation of delay in detection are 0.06 years and 0.025 years, respectively. The small values of mean and standard deviation of delay in detection indicate the usefulness of the proposed algorithm.

CONCLUSIONS

An algorithm is proposed for identifying time of corrosion initiation in reinforced concrete structures using on-line electrochemical noise data measured using ZRA technique. The algorithm is based on the maximum likelihood approach. Formulations are also made for the determination of window size and the threshold value for the decision function based on the signal-to-noise ratio. The usefulness of the algorithm is studied by using an example problem of identification of time of corrosion initiation in a reinforced concrete bridge girder, using simulated corrosion current data. The results indicate that proposed algorithm has desirable properties of online change point detection algorithms. The window size and the threshold value for the decision function determined in the study are specific to the problem considered. More studies are required to develop general guidelines on window size and the threshold value for the decision function to be used for reinforced concrete structural members in different exposure conditions. The studies presented in this paper will be useful while carrying out service life planning (by helping in planning maintenance/repair) and declaration and assessment of sustainability aspects (economic and social considerations by controlling the damage due to corrosion and helping in cost-effective maintenance and repair).

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