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Article

Experimental Study on A Reinforced Concrete Element to Extract the Durability Index with the Automated Visualization

Seyed Mohammad Sadegh Lajevardi[1], Fereidoon Moghadas Nejad[2*] and Mehdi Ravanshadnia[3]

[1]Department of Civil Engineering, Tehran Science and research branch, Islamic Azad University, Tehran, Iran
[2]Department of Civil and Environmental Engineering, Amirkabir University of Technology, Tehran, Iran
[3]Department of Civil Engineering, Tehran Science and research branch, Islamic Azad University, Tehran, Iran

ABSTRACT: Reinforced Concrete (RC) durability is a crucial feature to estimate the long-term quality and structural performance. The degradation model is vital for the resource planning of maintenance projects. This model will extract by updating the status of structures and trending the components' state over time in terms of durability. Surface erosion, spalling, cracks, and other defects exposed on the RC component lead to increase factors adversely affecting concrete durability in structures. This research presents an approach based on automated visualization for extracting quantitative indexes beside or instead of visual inspection without subjective interspersion of humans or probable human errors during the inspection. The durability index (D_i) will extract based on damage probability and its growth to extract the severity of failure and risk. Measurement operation by automated software has been double-checked by manual measurement tools, and data will verify randomly in this method. The result shows in this component, the damaged area increases by %24 after a definite time. According to degradation models, it shows this component may pass the relative thresholds as a limit state of operation to fail. This significant difference between expected time and designing time determines the D_i equal to 5 out of 10.

1. INTRODUCTION

Railway infrastructures network developed since immemorial days in industrial countries based on transferring load and passenger demands. Since passengers and infrastructure owners are the most substantial stakeholders, it is necessary to do several corrective actions in line with stakeholders' demands. For instance, based on operators' mandates and passengers' expectations, enhancing the convenience of travel and reducing time travel duration is essential. Therefore, automation in railway infrastructure quality control is an important factor in reaching mentioned goals with minimum risk for inspectors. Also, reducing the number of unexpected failures during operation leads to reducing the train emergency stops and increasing the number of successful travels. On the other hand, the ageing process over time leads to quality loss because of environmental aspects and chemical reactions inside the material. Thus, the condition of structures has to update in terms of quality. Meanwhile, routine inspections play a crucial role in maintenance activities [1].

For the first step, gathering data is remarkable for a researcher in the field of quality control. Based on intermittent train movement in short intervals, inspection during the operation is necessary for safety. However, many crises threaten the inspectors during the operation if they follow the traditional inspection. Defect growth estimation denoted by automatic monitoring method through various sorts of sensors prepares a database for finding the durability index. In this manner, structural health monitoring (SHM) methods update the structural member's state based on the prepared database [2]. SHM community, such as damage and crack detection using images, vibration indications, and abnormal measurement diagnosis [3]. For this manner, several sensors (such as humidity, temperature, pressure, load, potential hydrogen (PH), hardness, chemical composition, Acoustic emission (AE), and others) have been exploited for data gathering and damage detection [7, 13]. AE was used for damage monitoring in reinforced concrete structures [4,

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5]. In this manner, AE applies to highlight internal damage progress [6]. However, the complex fracture and defects could not be efficiently categorized and rating by measuring the deterioration with some sorts of monitoring methods such as visual sensors but these sensors could find surface defects and mechanical features [6]. One of the famous tests in concrete elements is a visual inspection for finding damages and automated visual inspection measures the defect growth. Since real-time monitoring is necessary for reliability assessment, automated visualization is an essential tool for inspectors to evaluate their objects without human wrongs along with regular inspections.

Analyzing data in automation systems has been done by researchers with intelligence approaches [16]. It has three levels desirable for SHM during the operation. The first level focuses on defect detection and alarm for the operator. The second level prepares a baseline for comparing elements and their priority. The third level will guide decision-makers to estimate and forecast their future demands by trending the statutes. In this manner, the Semantic Web layer doings as the "brain" to provide the basis for deciding about defects [9]. However, this research presents risk as a basic logic for automation in decision-making after image processing and data gathering.

Electrical conductivity is an item in terms of structural health monitoring methods to estimate the durability of reinforced concrete [11]. However, the durability of reinforced concrete after risk analysis is not connected with image processing based on degradation surface status within a time window. This research will focus on this gap to improve condition-based maintenance.

1.1. Structural health monitoring

Several tools such as ground penetrant radar (GPR), ultrasonic (UT) tools, X-ray tube, accelerometer, moisture meters, Linear Variable Differential Transformer (LVDT), Flat jack and other measuring tools are proper for finding the features of the structure. According to recent research, some of them are proper for finding the internal damage and some of them are proper for external damages based on features comparison before and after the degradation. To find the overall quality state of the structure, visual inspection was selected to compare other non-destructive tests (NDT). Visual inspection is not expensive, and it is proper to find the critical zones in the structure. This paper is not focused on expensive tools for monitoring the structure. Therefore, an automation visual test selects to develop the decision system at a lower cost in the software field [14]. Meanwhile, the software for data processing supports not only data extracted from a charge-coupled device (CCD) and supplementary metal-oxide-semiconductor (CMOS) sensor but also supports other sensors such as Ground Penetrating Radar (GPR) [8, 10]. Therefore, the visual sensor output is a type of signal for operators such as other structural health monitoring tools output.

Due to the development of the railroad network, automation in monitoring is avoidable for inspectors to precise planning and codification of defects type concerning the corrective action and their location [21,22]. Several studies try to develop decision support systems by processing data after collection action [26-30].

1.2. Durability

The durability of concrete may be defined as the concrete features to bear potential attack against chemical attack, crushing, weathering action, and abrasion based on the structure permeability for gas and water, absorptivity, initial absorption capacity, water tightness, diffusion, and the other [45]. Meanwhile, durable concrete maintains its desired engineering properties during the operation. For instance, the durability index for aggregate is a value which represents the relative resistance of this material to produce detrimental claylike fines when subjected to the suggested mechanical techniques of degradation [35]. The design service life of a structure would be prepared based on the requirement of the owner and operators. Service life for the important and large bridge may be

50 years to 100 years. [39]. Cutting-edge design for durability deals with the inherent uncertainties in material and environmental features [31, 32]. Non-destructive tests (NDT) assess the quality of concrete in terms of durability. Several common defects, such as corrosion of steel in concrete related to durability. Also, recent research shows some non-destructive electrochemical tools are useful and commonly used for monitoring these types of defects, especially in corrosion investigations. Electrical resistivity is an NDT tool to measure the durability of concrete along with its quality. The electrical resistance of an object is a measure of its opposition to the flow of electric current. This feature of concrete materials shows its durability based on voids connectivity [33, 34]. Presently, this research works aim at the D_i estimation and the possibilities of condition monitoring along with subsequent data gathering based on image processing tools. Therefore, this research prepares a maintenance plan for the case study based on SHM results and the extracted D_i according to the semantic approach. Finding critical elements in the structure and estimating their lifetime is the outcome of this maintenance plan. Finding critical elements in structure will mostly concern the filtering of the enormous data set in terms of quality. The rate of growth for progressive defects and cracks is a piece of evidence to find critical concrete elements in terms of their quality comparison. Several worthless and costly data will eliminate from the input data set with this approach. It means durable elements will not check in a short time by frequent inspection. Meanwhile, critical elements with expanding damages are important for inspectors and maintenance managers. Finally, the main contribution of this research work is presenting the relative index based on damage detection by monitoring their changes and representing optimised maintenance plans by considering the durability of concrete elements as well as other attitudes of quality and critical zones.

2. METHODOLOGY

Although the reliability index is a parameter that has been known to designers, this quantitative index has been neglected by maintenance managers. Risk assessment and related reliability index is a parameter that allows supporting the infrastructure owners to prepare a decision support system for their corrective activities. To measure damage propagation, it is inevitable to use automation tools with quantitative results. This research focuses on extracting the risk index to estimate a segment of degradation model of concrete elements in terms of their durability. Since this research aims to combine automated damage detection of RC components with risk severity and durability content, it is necessary to consider several image processing and technical limit state of concrete elements. Therefore, this research applies several tools to the aim of finding D_i as follows.

2.1. Software and hardware details for SHM

According to Eurocode 2 and ACI 224R-0, the limit state of crack width was considered 0.3 mm [17, 18, and 46]. Moreover, RC components with spalling defects as well as exposed rebar have a risk for RC structure durability. Therefore, based on an initial visual test, the selected object for this research has the potential risk in terms of the probability of defect for this RC structure. The monitoring set-up for the RC component is illustrated in figure1. The equipment detail in this figure explains in detail in figure 4.

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Figure 1. Data gathering process.

The case study location was located at the end of the bridge's abutment. This is a non-level intersection of the railway network and road bridge placed in the west urban area of the Tehran subway. The drainage barbican is not adequately isolated from the concrete surface, and the wastewater in the urban area leads to carbonation and damage propagation during the operation.

While gathering data, the camera has to fix under natural lighting on a sunny day. Data gathering has been done by a camera with a CMOS sensor and 22.3 x 14.9 mm dimension. Specification of computer processors and language programing during the data analysis are as follows.

- ✓ Core i7 Processors
- ✓ 16 GB of random access memory (RAM)
- ✓ C# Programming language

This research desired to find the damage propagation based on automated visual inspection. Therefore, edge detection has been applied to detect and measure the damaged area to estimate the durability index. Edge detection steps are as follows [36].

- ✓ Filtering and Enhancement - Filter image to improve the performance of the edge detector.
- ✓ Detection - Finding edges by defining the threshold with the minimum thickness (1pixel)
- ✓ Localization - locate the edge accurately in the photo

2.2. Image processing method

In computer vision, different methodologies have been exploited to solve practical problems, such as object detection. An object to detect displacement of an element or damaged area in a structural component [42]. Surface cracks and surface foreign objects can simply make a large number of incorrect edge detections when the fringe phenomenon generates by the uneven distribution by exploiting a typical differential edge detector. Therefore, it was necessary to design a detection operator that is capable to reduce the noise [12, 41]. Kayyali, Harris & Stephens / Plessey / Shi–Tomasi, SUSAN, Shi & Tomasi,

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Level curve curvature, FAST, Laplacian of Gaussian, Difference of Gaussians, Determinant of Hessian, MSER, PCBR, Grey-level blobs, Automated, Independent component analysis, Isomap, Latent semantic analysis, Partial least squares, Semidefinite embedding, Auto-encoder, Nonlinear dimensionality reduction, and Principal Component Analysis (Kernel PCA and Multilinear PCA) are the methods which have been applied for image processing. Some of the most important methods for data analysis are as follows.

2.2.1. Canny

Canny's edge recognition algorithm is a conventional technique for edge detection in grey-scale images [40]. After noise reduction, it is necessary to enhance the quality of the extracted image from the previous step with a smooth mathematical tool called Gaussian. Also, detection and localization criteria, it has been done based on the formula as follows. First of all, every signals transfer to noise ratio and then localizes criteria. Let the impulse response of the filter be $f_{(x)}$, and denote the edge itself by $G_{(x)}$. Then the response of the filter to this edge at its centre H_G is given by a convolution integral [36]. Assuming the filter has a finite impulse response bounded by [-W, W].

$$H_G = \int_{-W}^{+W} G_{(x)} f_{(x)} dx \quad \textit{(Equation 1)}$$

This method detects by extract useful structural information from various vision objects and dramatically reduce the amount of data to be processed. The two significant features of this technique are development with double thresholding of the gradient image and Non-Maximum Suppression [19].

2.2.2. Fuzzy operator

Edge pixels are recognized by evaluating local change in intensity followed by thresholding. The change in intensity may be measured by defining the first derivative of the image function. The rate of change of a 2D image intensity function f (x,y) is given by the gradient vector as follows[37].

$$\nabla f = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} = \begin{bmatrix} G_x \\ G_y \end{bmatrix} \quad \textit{(Equation 2)}$$

Where G_x and G_y indicate the rate of intensity change along the horizontal (x-axis) and vertical (y-axis) directions. The rate of the gradient vector ∇f, referred to the rate of change in intensity at the pixel location (x, y) as follows.

$$G(x, y) = \sqrt{G_x^2 + G_y^2} = \sqrt{(\frac{\partial f}{\partial x})^2 + (\frac{\partial f}{\partial y})^2} \quad \textit{(Equation 3)}$$

This method has been used for detecting defects after imaging in the industry [23]. Also, this attitude is a developed intelligence-supportive system for decision-making and classification [24].

In this research, damage detection and data processing have been done with this logical tool to obtain the D_i for the RC component. This technique presents the best results with the highest resolution to compare other remain mentioned techniques to check the damage propagation rate

2.2.3. Sobel operator

This operator is a tool for image processing and cracks recognition. It has been applied for eliminating isolated noise spots, extracting the crack edge evidence and improving the positioning accuracy of the crack boundary. Furthermore, according to the image

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feature of the bridge crack edge, the target crack is identified and classified by this method. [20]

This mask has been assumed for estimating the edge strength at every pixel point in the input image. Therefore, the intensity gradients G_x and G_y along the horizontal and vertical directions, are determined at every pixel (x, y) in the image. The kernels can be exploited discretely to the input image, to produce separate measurements of the gradient component in each orientation (call these G_x and G_y).

$$|G| = \sqrt{G_x^2 + G_y^2} \quad \textit{(Equation 4)}$$

$$\theta = arctan(\frac{G_y}{G_x}) \quad \textit{(Equation 5)}$$

Orientation 0 is taken to mean that the direction of maximum contrast from black to white runs from left to right on the image, and other angles are measured anti-clockwise from this [38].

2.2.4. Prewitt operator

The Prewitt kernels are simpler to implement than the Sobel kernels, but the slight computational difference between them typically is not an issue. [38] Prewitt technique is a proper tool for data process based on the results of intensity function. The outcomes of this technique were applied for edges detection where the gradient of intensity function has extreme value [25].

2.2.5. Research operators

In this research after preparation of the grey scale from a pure image, the Fuzzy, the Sobel and then the Perwitt operator were exploited for damage detection extraction. Since these methods and operators have been applied in recent research, they have been exploited to find the dimension of the damage in the present research. Based on this step, output damage propagation will estimate the severity of failure and D_i in the bridge.

2.3. Probabilistic-based structural assessment

Based on the RC elements limitation, it is possible to assess the durability of RC. For this reason, the probability of failure for the component would be calculated in this segment.

2.3.1. Probability of failure

In this research, the probability of failure illustrates a defect in the overall view of the bridge, but it is a failure for a component. It means failure of structural members is not necessarily lead to overall structure failure because it might be possible to transfer load relies on other parallel structural members.

2.3.2. Severity of failure

Defect propagation is a sign of the severity of failure (Sf) during the operation for risk assessment. In this research, it is desirable to present the possibility of application severity with image processing tools to compare defect growth during the operation.

2.4. Risk assessment

The risk index has been calculated by multiplying severity grades with the probability of defects. To do this end, the relative durability index would be calculated based on the risk index as follows steps in figure 2.

$$Risk = P_f \times S_f \quad \textit{(Equation 5)}$$

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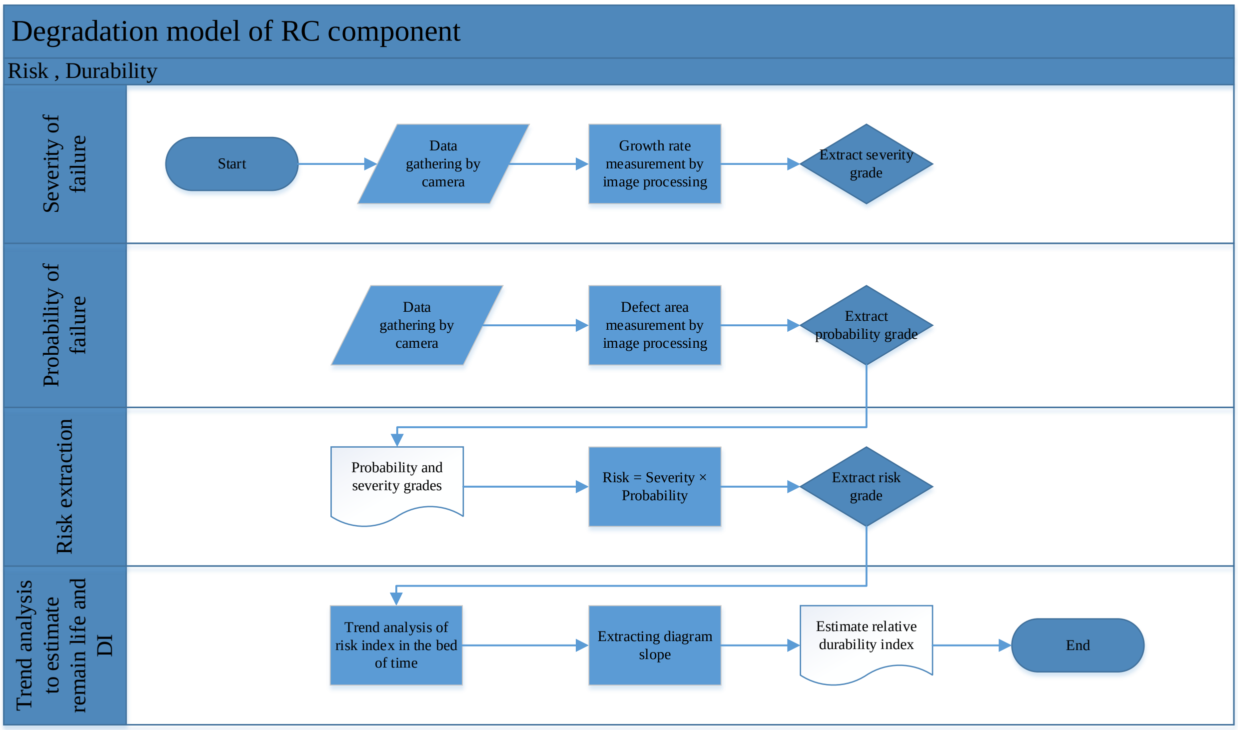

Figure 2. Research method.

3. Research case study

Automated visualization, evaluate the RC structural elements in terms of their quality the same as experience inspectors' judgment. Furthermore, this method has measurable tools more than the traditional visual inspection to extract risk as a relative index to compare bridges and their RC elements. This comparable index based on quantitative outputs will extract the durability index by using image processing tools. Hence, this approach would be used as a practical replacement for experienced observers and inspectors, especially in the subway with frequent loads and a short time for maintenance activities. Also, it is possible to double-check with random by qualitative traditional inspection. For this manner, 7 RC bridges have been selected from the Tehran subway and critical component has been defined by pre-posterior analysis. In the end, the analysis focused on the high-risk case for extracting the durability index based on the proposed method.

3.1. Experimental tests

The first step of this study is gathering data from the object. Other steps of the research process have been shown in figure 3. Also, this process will repeat to find other points of structure status based on linking the status points over time and estimate the degradation model with the local slope.

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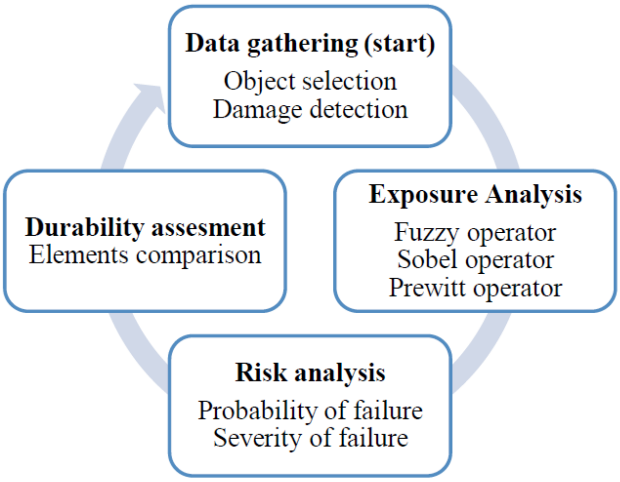

Figure 3. Research process.

3.1.1. Data gathering

Data gathering with the fixed camera in terms of height and location on the ground has been done twice over time. This setup and the objects of the case study have been illustrated in figure 4.

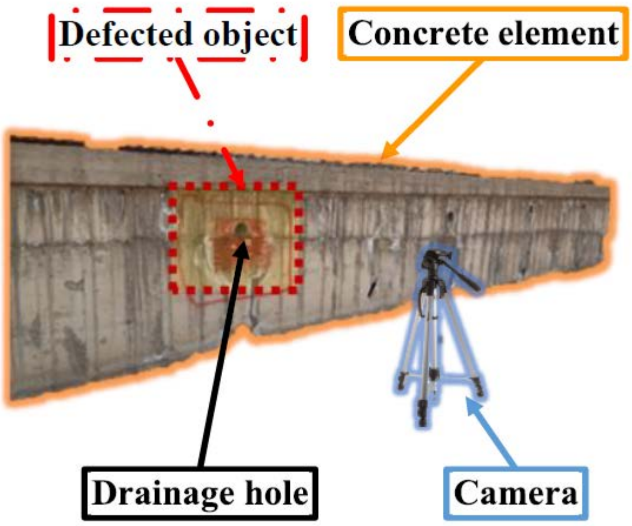

Figure 4. Case study object - RC element.

For fixing the camera on the ground, the location of its stand had been marked for the second data gathering. Also, the drainage hole has a potential place for defect expansion and extracting the durability index due to these changes. After a comparison between images, significant changes are existing between the first data gathering and the second imaging determined for the research aim.

The RC elements might be damaged on the surface due to several environmental reasons, poor construction quality, bad curing and some other internal and chemical attack reasons. These surface damages are as follows.

- Cracking
- Crazing
- Blistering

- Delamination
- Dusting
- Curling
- Efflorescence
- Scaling and spalling

It is necessary to mention these surface damages are considering a threat to concrete durability.

3.1.2. Exposure analysis

After data gathering and pre-posterior analysis, it is necessary to analyze surface damages to assess exposed defects. The critical zone has been selected based on initial data gathering and abutment of this bridge. The durability feature has a direct link with the surface defect and drainage location has a potential place for surface damage. The traditional method relies on subjective interpretation based on visual inspection. Meanwhile, image processing software monitors the rate of defect expansion. Figures 5-A and 5-B illustrate the result of this analysis.

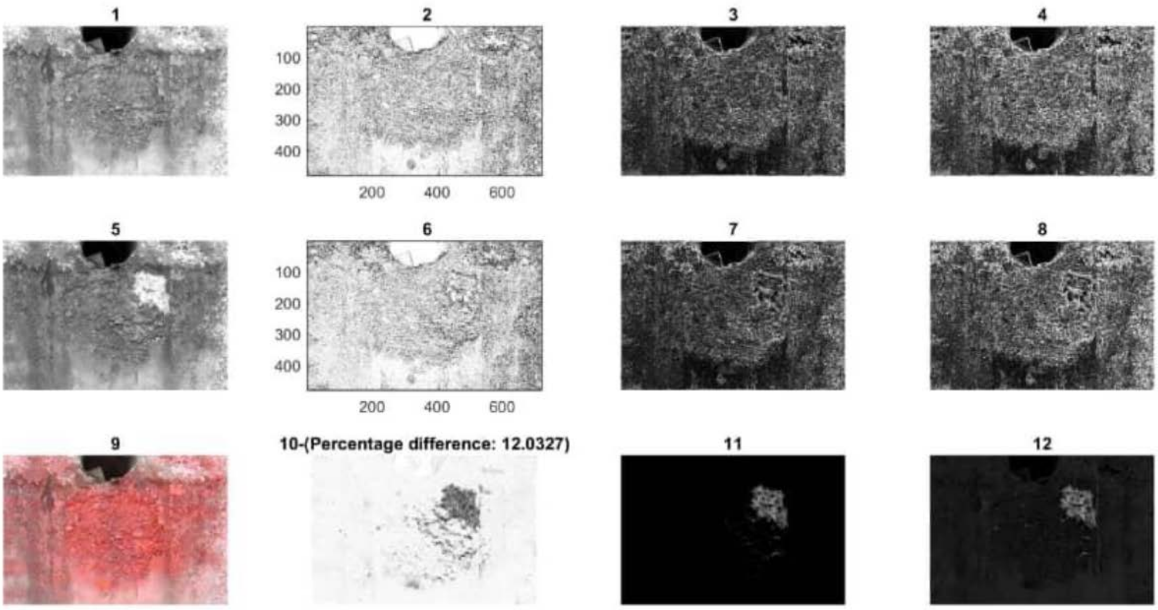

Figure 5. (A) - Surface concrete with a minor defect

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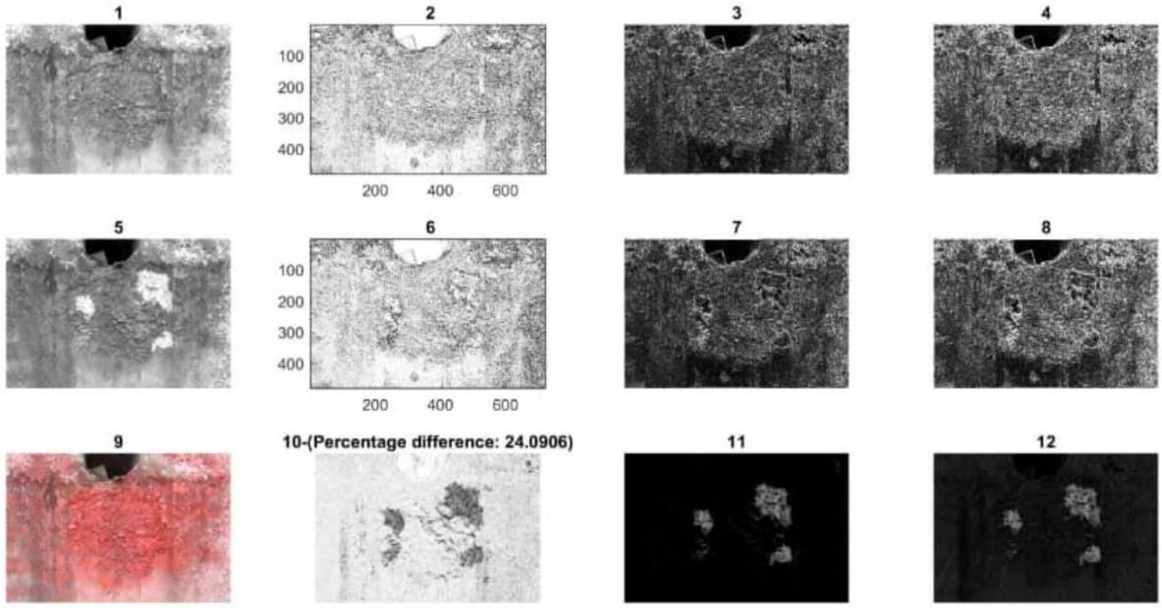

Figure. 5(B) - Surface concrete with a major defect

Measurement of the damaged area has been done by automated software in this research. Although the surface of the concrete is intact at the first step of data gathering, this zone is exposed to wastewater due to poor drainage design and damage over time.

Therefore, the first row in Figures 5-A and B concerning intact concrete before surface damage at the first step of gathering data. The second row in both pictures demonstrated the damaged surface over time. Therefore, the damages reveal after a short time based on figure 5-A, which has minor damage over time. Figure 5-B has significant defects for a longer time to compare the first image. The third row is a result of a comparison between intact concrete and damaged concrete over time. Since the first time gathering data based on figure 5-A has a minor defect in a short time, the damaged area is lower than the second time of gathering data in figure 5-B after a longer time. Also, the first column in figure 5-A and figure 5-B demonstrate the greyscale and pure image of the object without noises. The second column shows the result of image processing by fuzzy logic. The third column illustrates the image processing analysis and comparison by the Sobel algorithm, and finally, the fourth column is the output of the comparison by the Perwitt operator. The software output comprises a comparison between damaged and intact surfaces and it will verify by double-checking with manual measurement tools.

3.1.3. Discussion

In this research, 7 RC bridges have been selected and checked from the Tehran subway railway network. The riskiest bridge has been selected for detailed inspection and monitoring of the state over time.

3.1.3.1. Probability of failure (P_f)

For extracting the probability of failure, it is possible to count the number of defects in each component divided by their approximate volume, and the probability of failure (Pf) is updatable in each time window. For finding a critical case, 7 RC bridges have been checked during Pre-posterior analysis. The probability of failure in each bridge was calculated based on their approximate volume according to table 1.

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Table 1. – Approximate volume of elements for risk assessment.

Bridge	Pier type	Span number	Average span length (m)	Abutment height (m)	Bridge width (m)	Bridge length (m)	Deck area (m^2)	Material volume (m^3)
1	**-**	**1**	**15.6**	**4**	**12**	**15.6**	**187.2**	748.8
2	Wall, Single pier	1	15.6	5	9.14	15.6	142.584	712.92
3	Several in each section, Cylinder ,	5	15.6	3	9.06	78	706.68	5653.44
4		1	15.6	4	9.1	15.6	141.96	709.8
5	Several in each section, Cylinder ,	1	19.8	7	12	79.2	950.4	6652.8
6	Several in each section,	1	15.6	12	9.13	15.6	142.428	854.568
7	-	1	12.6	6	9.06	12.6	114.156	684.936

Based on the approximate volume and the quantity of damaged area on that material, the probability of failure in each element has been estimated as it has been shown in tables 2, 3-A and 3-B during the visual inspection.

Table 2. Superstructure probability of failure for risk assessment.

Bridge	Number of damaged area on deck			Failure density of deck	Probability of failure (Deck) 0-1
	Barrier	Beam	Drainage		
1	0	0	0	0	0
2	0	1	0	0.007013	0.118714
3	0	2	2	0.00566	0.095809
4	0	2	1	0.021133	0.357706
5	1	2	1	0.004209	0.07124
6	0	2	1	0.021063	0.356531
7	0	0	0	0	0

Table 3. (A) – Probability of failure for Substructure part 1.

Bridge	Elements of abutment		
	Number of damaged area	Failure density of Abutment	Probability of failure (Abutment) 0-1
1	**0**	**0**	0
2	0	0	0
3	1	0.25	0.5
4	0	0	0
5	1	0.25	0.5
6	0	0	0
7	0	0	0

Table 3. (B) – Probability of failure for Substructure part 2.

Bridge	Foundation			Elements of pier	
	Number of damaged area		Probability of failure (Foundation) 0-1	Number of damaged area	Probability of failure (Pier) 0-1
	Pedestal	Footing		Elastomeric bearing	
1~7	**0**	0	0	0	0

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Therefore, after finding the critical component of the bridges based on P_f it is possible to find S_f according to the results of automated visual inspection and then it is possible to calculate the risk and durability index with a linear implement of S_f along different time intervals during the operation.

The results based on figure 5 were analysed according to estimate damage growth and critical zone severity for risk. The rate of damage growth in critical elements based on damage expansion has been presented in table 4 for the critical bridge's component in table 3.

3.1.3.2. Severity of failure (S_f)

Therefore after finding the critical component of the bridges based on P_f it is possible to find S_f according to the results of automated visual inspection and then it is possible to calculate risk and durability index.

The results based on figure 5 were analysis according to estimate damage growth and critical zone severity for risk. The rate of damage growth in critical element based on damage expansion present in table 4 for critical bridge's component in table 3.

Table 4. – Damage growth in abutment of critical bridge element.

No	Year	Month (T)	Damage growth (S_f)	P_f	Risk (R_t)
1	0	0	0	0.5	-
2	0.25	3	0.12		0.6
3	0.5	6	0.24		0.12
4	1	12	0.48 (Estimation)		0.24

These results present the severity of failure in the critical element of the bridge with the highest P_f.

3.1.3.3. Risk grades and durability index

Since durability as time-dependent probabilistic reliability may be prolonged by repairs of materials and components, it is necessary to consider momentary durability [47]. Meanwhile, according to figure 6 RC components' degradation intensity status will change over their period of life. It means the durability index has to change in each period not only based on repair activities but also according to their period of life.

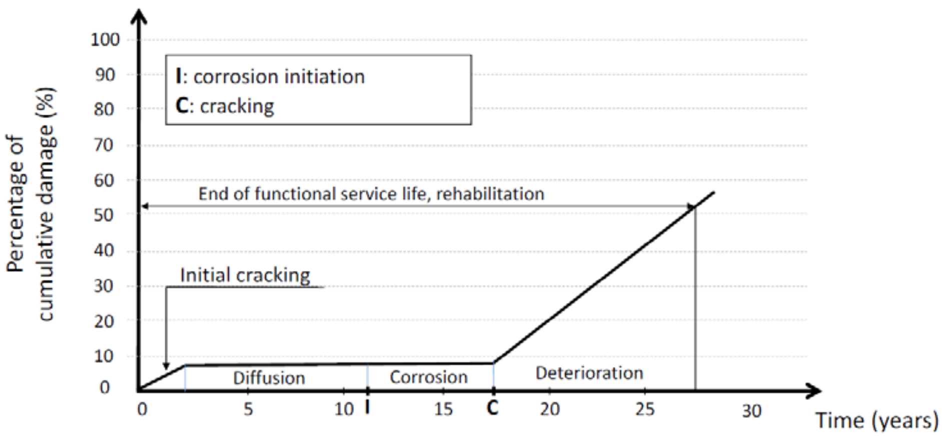

Figure 6. Degradation of reinforced concrete [43].

Therefore, in this research, it is desirable to estimate the tangent line of the function for the degradation model of RC element in a short period of definite time [43, 44]. To this end, the durability index estimate by the function of risk over time is as follows.

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$$D_i = \frac{dR_t}{dt} \quad \textit{(Equation 6)}$$

3.1.3.4. Results of case study analysis

The degradation model of the RC component is dependent on the durability index and the durability index has a relation to the risk over time. Based on recent data extracted from the case study within a short time, the function of the tangent line is as follows.

$$Y - R_2 = \left(\frac{R_2 - R_1}{T_2 - T_1}\right) X - T_2 \quad \textit{(Equation 7)}$$

In this formula, the damage will expand through life. If "Y" is RC component status in terms of degradation and "X" is a variable based on time, the degradation model estimates are based on momentary durability. Therefore, the risk of operation will change over time and "T" represents time in terms of the month. "R" denotes the risk based on damage growth in the element during the operation and the slope of the line represents the D_i in each segment

4. CONCLUSION

This research proposed an approach to estimate the output of the degradation model based on the durability index according to the potential risk concerning input data (S_f and P_f). The degradation model is useful to assign the corrective actions for the risky RC components during emergency conditions. It is also necessary the planning frequent inspection and preventive maintenance in terms of RCM for quality control of infrastructures.

After Pre-posterior analysis and defining the risky RC component, the degradation model was estimated based on the durability index. Based on the image processing results, the damage growth rate is %24 during the definite time in this load-bearing RC component. If this definite time considers 6 months, this case has 3 milestones during the test. The first data gathering was done from the intact RC component and the second milestone simultaneously with the initial damage growth with %12 damage growth. Meanwhile, the final and third milestone with %24 of damage measured by this proposed method. If the severity and probability consider for risk, the component durability index will extract based on variable reliability through the life as a degradation model during the operation. In other words, if service limit and ultimate limit consider as thresholds in the degradation model, it is possible to estimate the next step for the structure status based on the degradation models and compare the next step of structure status with the expected structure status [39]. In this case, the D_i was estimated at 0.02 for the definite time of inspection as a momentary durability index to estimate the degradation model.

Image processing has been exploited as a tool to reach the research aim. Meanwhile, this research not only compares the operators of image processing but also combines the data gathering with mathematical tools and a statistical approach in terms of the risk concept. Merging the data processing in terms of vulnerable zones with image processing tools for finding the maximum difference between the image processing operators in each element helps the user to decide on maintenance planning with the hybrid approach. Also, this comparison approach maximises the value of information after data gathering by the image processing operator.

Finding the damage growth and estimating the degradation trend is not possible by traditional visual inspection. More than the proposed structural health monitoring tools for data gathering, this quantitative method estimates the status of reinforced concrete without individual perception. Therefore, regardless of that human error elimination, the computer aid records data and trends those data with a risk logic concept to prioritize the vulnerable zones based on their degradation rate.

5. DATA AVAILABILITY STATEMENT

All data that support the findings of this study are available from the corresponding author upon reasonable request. Also, all data during the study appear in the submitted article.

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7. REFERENCE

1. Agnisarman, S., Lopes, S., Chalil, K., & Piratla, K. (2019). Automation in Construction A survey of automation-enabled human-in-the-loop systems for infrastructure visual inspection. Automation in Construction, 97(November 2018), 52–762. Hui, L. I., & Jinping, O. U. (2011). Structural Health Monitoring : From Sensing Technology Stepping to Health Diagnosis. Procedia Engineering, 14, 753–760. https://doi.org/10.1016/j.proeng.2011.07.095
3. Fan, G., Li, J., & Hao, H. (2020). Vibration signal denoising for structural health monitoring by residual convolutional neural networks. Measurement, 157, 107651. https://doi.org/10.1016/j.measurement.2020.107651
4. Behnia, A., Kian, H., Mousa, A. A., & Alireza, S. (2019). A novel damage index for online monitoring of RC slabs under monotonic loading by integration of process controlling into acoustic emission technique. Mechanical Systems and Signal Processing, 119, 547–560.
https://doi.org/10.1016/j.ymssp.2018.09.030
5. Bagherifaez, M., Behnia, A., Majeed, & Kian, C. H. (2014). Acoustic Emission Monitoring of Multicell Reinforced Concrete Box Girders. The Scientific World Journal,2014, https://doi.org/10.1155/2014/567619
6. Tsangouri, E., Remy, O., Boulpaep, F., Verbruggen, S., Livitsanos, G., & Aggelis, D. G. (2019). Structural health assessment of prefabricated concrete elements using Acoustic Emission : Towards an optimized damage sensing tool. Construction and Building Materials, 206, 261–269. https://doi.org/10.1016/j.conbuildmat.2019.02.035
7. Taheri, S. (2019). A review on five key sensors for monitoring of concrete structures. Construction and Building Materials, 204, 492–509. https://doi.org/10.1016/j.conbuildmat.2019.01.172
8. Zhang, J., Yang, X., Li, W., Zhang, S., & Jia, Y. (2020). Automation in Construction Automatic detection of moisture damages in asphalt pavements from GPR data with deep CNN and IRS method. Automation in Construction, 113(September 2019), 103119. https://doi.org/10.1016/j.autcon.2020.103119
9. Biswas, R., & Sil, J. (2012). An Improved Canny Edge Detection Algorithm Based on Type-2 Fuzzy Sets. Procedia Technology, 4, 820–824. https://doi.org/10.1016/j.protcy.2012.05.134
10. Dinh, K., Gucunski, N., & Zayed, T. (2019). NDT and E International Automated visualization of concrete bridge deck condition from GPR data. NDT and E International, 102(November 2018), 120–128. https://doi.org/10.1016/j.ndteint.2018.11.015
11. Wang, Y., Liu, K., Wang, C., & Zhou, S. (2022). Influence of solution concentration and temperature on the repair effect for electrophoretic deposition of rust-cracked reinforced concrete. Journal of Building Engineering, 56(June), 104772. https://doi.org/10.1016/j.jobe.2022.104772
12. Zhang, D., Xu, X., Lin, H., Gui, R., Cao, M., & He, L. (2019). Automation in Construction Automatic road-marking detection and measurement from laser-scanning 3D profile data, 108(November 2018). https://doi.org/10.1016/j.autcon.2019.102957
13. Yun, H., Choi, W., & Seo, S. (2010). NDT & E International Acoustic emission activities and damage evaluation of reinforced concrete beams strengthened with CFRP sheets. NDT and E International, 43(7), 615–628. https://doi.org/10.1016/j.ndteint.2010.06.006
14. Tabiai, I., Tkachev, G., Diehl, P., Ertl, T., Therriault, D., & Lévesque, M. (2019). Hybrid image processing approach for autonomous crack area detection and tracking using local digital image correlation results applied to single- fi ber interfacial debonding, 216(November 2018). https://doi.org/10.1016/j.engfracmech.2019.106485
15. Mahmoud R. Halfawy, J. H. (n.d.). 15-SHM-Image processing. Infrastructure Systems. https://doi.org/https://ascelibrary.org/doi/10.1061/%28ASCE%29IS.1943-555X.0000161
16. Li, D., Cong, A., & Guo, S. (2019). Automation in Construction Sewer damage detection from imbalanced CCTV inspection data using deep convolutional neural networks with hierarchical classi fi cation. Automation in Construction, 101(June 2018), 199–208. https://doi.org/10.1016/j.autcon.2019.01.017
17. Technical, S. d'études techniques des routes et autoroutes, & Department for Transport, R. and B. (2007). Guide_EC2_EN (Eurocode 2 application to concrete highway bridges).
18. ACI 224R-01. (2001). Control of Cracking in Concrete Structures Reported by ACI Committee 224. ACI 224R-01. ACI Committee 224R-01, 1–46. https://doi.org/0097-8515
19. Biswas, R., & Sil, J. (2012). An Improved Canny Edge Detection Algorithm Based on Type-2 Fuzzy Sets. Procedia Technology, 4, 820–824. https://doi.org/10.1016/j.protcy.2012.05.134

20. Chen, Z. P., Guang, C., Wang, Y., & Zhang, J. Y. (2019). Research crack detection of algorithm of the concrete bridge based on image processing. The innovation Protecting cultural based in on image processing heritage the Procedia Computer Science, 154, 610–616. https://doi.org/10.1016/j.procs.2019.06.096
21. Nejati, A., Ravanshadnia, M., & Sadeh, E. (2018). Selecting an Appropriate Express Railway Pavement System Using VIKOR Multi-Criteria Decision Making Model, 4(5), 1104–1116.
22. Jadidi, H., Ravanshadnia, M., Hosseinalipour, M. et al. A step-by-step construction site photography procedure to enhance the efficiency of as-built data visualization: a case study. Vis. in Eng. 3, 3 (2015). https://doi.org/10.1186/s40327-014-0016-9
23. Amza, C. G., & Cicic, D. T. (2015). Industrial image processing using fuzzy-logic. Procedia Engineering, 100(January), 492–498. https://doi.org/10.1016/j.proeng.2015.01.404
24. Fageth, R., Allen, W. G., & Jäger, U. (1996). Fuzzy logic classification in image processing. Fuzzy Sets and Systems, 82(3), 265–278. https://doi.org/10.1016/0165-0114(95)00235-9
25. Lakhani, K., Minocha, B., & Gugnani, N. (2016). Analyzing edge detection techniques for feature extraction in dental radiographs & Perspectives in Science, 8, 395–398. https://doi.org/10.1016/j.pisc.2016.04.087
26. Firas Shalabi, S.M.ASCE; and Yelda Turkan, Aff.M.ASCE. (2016). IFC BIM-Based Facility Management Approach to Optimize Data Collection for Corrective Maintenance, Journal of performance of constructed facilities, 31(1), https://doi.org/10.1061/(ASCE)CF.1943-5509.0000941
27. Chong HY., Wang J., Shou W., Wang X., Guo J. (2014) Improving Quality and Performance of Facility Management Using Building Information Modelling. In: Luo Y. (eds) Cooperative Design, Visualization, and Engineering. CDVE 2014. Lecture Notes in Computer Science, vol 8683. Springer, Cham. https://doi.org/10.1007/978-3-319-10831-5_6
28. Boukamp, F., & Akinci, B. (2007). Automated processing of construction specifications to support inspection and quality control. Automation in Construction, 17(1), 90–106. https://doi.org/10.1016/j.autcon.2007.03.002
29. Kim, M. K., Wang, Q., Park, J. W., Cheng, J. C. P., Sohn, H., & Chang, C. C. (2016). Automated dimensional quality assurance of full-scale precast concrete elements using laser scanning and BIM. Automation in Construction, 72, 102–114. https://doi.org/10.1016/j.autcon.2016.08.035
30. Singh, V., Gu, N., & Wang, X. (2011). A theoretical framework of a BIM-based multi-disciplinary collaboration platform. Automation in Construction, 20(2), 134–144. https://doi.org/10.1016/j.autcon.2010.09.011
31. Vořechovská, D., Teplý, B., & Chromá, M. (2010). Probabilistic Assessment of Concrete Structure Durability under Reinforcement Corrosion Attack. Journal of Performance of Constructed Facilities, 24(6), 571–579. https://doi.org/10.1061/(asce)cf.1943-5509.0000130
32. Zou, D., Wang, Z., Shen, M., Liu, T., & Zhou, A. (2021). Improvement in freeze-thaw durability of recycled aggregate permeable concrete with silane modification. Construction and Building Materials, 268, 121097. https://doi.org/10.1016/j.conbuildmat.2020.121097
33. Azarsa, P ., & Gupta, R. (2017). Resistivity of Concrete for Electrical Durability Evaluation: A Review. Advances in Materials Science and Engineering, 2017, 1–30. https://doi.org/10.1155/2017/8453095
34. Carino Nicholas J, (1999) Nondestructive Techniques to Investigate Corrosion Status in Concrete Structures, Journal of Performance of Constructed Facilities, 13(3), 96–106, https://doi.org/10.1061/(ASCE)0887-3828(1999)13:3(96)
35. AASHTO T 210-91 (2015). Durability index of aggregates. American Association of State and Highway Transportation Officials.
36. Canny, J. (1986). A Computational Approach to Edge Detection. IEEE Transaction on pattern analysis and machine intelligence, (6).
37. Khunteta, A., & Ghosh, D. (2014). Edge Detection via Edge-Strength Estimation Using Fuzzy Reasoning and Optimal Threshold Selection Using Particle Swarm Optimization. Advances in Fuzzy Systems. https://doi.org/http://dx.doi.org/10.1155/2014/365817
38. R. Gonzalez and R. Woods Digital Image Processing, Addison Wesley, 1992, pp 414 - 428.
39. The international organization for standardization. Durability — Service life design of concrete structures (ISO 16204), (2012). Geneva, Switzerland: International standard.
40. Spencer, B. F., Hoskere, V., & Narazaki, Y. (2019). Advances in Computer Vision-Based Civil Infrastructure Inspection and Monitoring. Engineering, 5(2), 199–222. https://doi.org/10.1016/j.eng.2018.11.030
41. Mahler, D.S., Kharoufa, Z.B., Wong, E.K. and Shaw, L.G. (1991), Pavement Distress Analysis Using Image Processing Techniques. Computer-Aided Civil and Infrastructure Engineering, 6: 1-14. https://doi.org/10.1111/j.1467-8667.1991.tb00393.x
42. Almeida, G., Melício, F., Biscaia, H., Chastre, C. and Fonseca, J.M. (2016), In-Plane Displacement and Strain Image Analysis. Computer-Aided Civil and Infrastructure Engineering, 31: 292-304. https://doi.org/10.1111/mice.12127
43. Liu, Y., & Weyers, R. E. (1999). Modeling time-to-corrosion cracking in chloride contaminated reinforced concrete structures. ACI Materials Journal. Virginia.
44. El Hajj, B. (2015). Probabilistic Modelling of Multiphasic Degradations for Maintenance Optimization of Infrastructures in Civil Engineering. Blaise Pascal.
45. Stehlík, M. (2014). Enhancing the durability of concrete made of concrete recyclate by additives and admixtures. Journal of Civil Engineering and Management, 20(2), 270–279. https://doi.org/10.3846/13923730.2013.802708
46. Jokūbaitis, A., Valivonis, J., & Marčiukaitis, G. (2016). Analysis of Strain State and Cracking of Cocnrete Sleepers. Journal of Civil Engineering and Management, 22(4), 564–572. https://doi.org/10.3846/13923730.2016.1147494

47. Kliukas, R., & Kudzys, A. (2004). Probabilistic durability prediction of existing building elements. Journal of Civil Engineering and Management, 10(2), 107–112. https://doi.org/10.1080/13923730.2004.9636294