Scientific paper

Quantitative Deterioration Assessment of Road Bridge Decks Based on Site Inspected Cracks under Stagnant Water
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Abstract

Stagnant water on reinforced concrete (RC) decks shortens their fatigue life significantly compared to dry conditions. By using a multi-scale simulation together with the pseudo-cracking method, the remaining fatigue life of real RC bridge decks covered by stagnant water is estimated based upon their site-inspected surface crack’s patterns. For quick diagnosis for deterioration magnitude of RC decks, two assessment methods are proposed. A predictive correlation of the remaining fatigue life and a mechanics-based parameter (cracks density) considering both cracks length and width is introduced as a speedy judgment for the deterioration-magnitude. For comprehensive judgment for the deterioration-magnitude, an artificial neural network (ANN) model is further introduced by means of machine learning. Bayesian regularization technique was conducted to the training scheme to reduce the misguided ANN’s evaluation caused by overlearning. Finally, deck’s bottom surface map of reference is introduced to show the location of comparatively problematic cracks based upon the weights assigned with the synapses of the neuron of the built ANN model.

1. Introduction

The effect of stagnant water like rainfall on bridge reinforced concrete (RC) decks has been investigated to be significant on their fatigue life (Matsui 1987; Waagaard 1982). It is reported that the existing residing condensed water in concrete weakens the performance of concrete in comparison with a dry state. The reduction of concrete's strength due to moisture is discussed qualitatively by changing surface energy of CSH binders, and accelerated wearing of the crack surfaces is identified by the cyclic shear experiments in pure water. As water inside concrete is hard to disperse under rapid deformation, the pore water pressure experiences sharp rises and/or falls. Several fatigue experiments in wet conditions were conducted and it was reported that water to crack interaction leads to negative impacts on the fatigue performance of concrete in compression.

If the drainage system does not work, water from rainfalls can pool over the concrete and infiltrate through the cracks, which causes severe damage combined with the fatigue loading from the heavy traffic as shown in Fig. 1. The pavement layer prohibits the bridge inspectors to examine the top surface’s damage of RC decks. Also during the renewal of pavement layers, heavy machines for removing the pavement overlay cause damage of concrete surfaces during the removal procedures. In 2015, it was reported that 70% of the road bridge decks in the USA is concrete (Ohta et al. 2015), which is not covered by thick pavement layers but just thin coating to protect the concrete surface from wearing and abrasion. Thus, water can flow easily to the drainage system as shown in Fig. 1. On the contrary, this strategy has been less applied in Japan. Some practitioners proposed using waterproof works to protect the concrete from stagnant water, but we shall keep in mind that the life of such kind of waterproof works has been less than the life of structure. Thus, periodical proof works and renewals have been inevitable in practice.

It is reported that stagnant water on RC decks causes shortened fatigue life significantly about 1/200 of the dry condition (Matsui 1987). Moreover, RC decks experience lattice cracks from heavy traffic loads. This combined effect on the life of RC decks should be investigated. Here, the multi-scale simulation can deal with crack to water interaction under repeated loads and it has been validated (Maekawa and Fujiyama 2013a, 2013b; Maekawa et al. 2015). By integrating the multi-scale simulation and the pseudo-cracking method, which can include the initial damage to RC decks (Fujiyama et al. 2011; Fujiyama et al. 2013; Tang et al. 2013), the remaining life of the existing RC decks can

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Fig. 1 Stagnant water versus flowing water on RC decks.
be obtained for a rational maintenance plan. By utilizing the data assimilation (Tanaka et al. 2017; Fathalla et al. 2018a, 2018b), the authors introduced two methods for the deterioration-magnitude assessment of the RC decks from their inspected cracks as shown in Fig. 2; one is the predictive correlation in use of the mechanics-oriented parameter (cracks density) and the other is ANN model.

First, in this research, the remaining fatigue lives of existing RC decks are analyzed for various crack patterns by using data assimilation technology in order to check the range and the trend of their fatigue lives. After that, the authors tried to build the ANN model based on artificial crack patterns due to the biased fatigue lives of the real crack patterns, where their fatigue lives do not cover whole ranges of fatigue life. To meet that challenge, randomized artificial crack pattern program (RACP) is introduced to build the training dataset by filling up the gaps of site inspection database (Fathalla et al. 2018b). In this study, real site crack patterns will be used only once at the final step to test the generalization of the proposed evaluation methods.

Second, on the basis of the simulation results, an acceptable correlation, regarding fatigue problems, is proposed between the remaining fatigue life and a mechanical-based parameter (cracks density) of the bottom surface cracks by considering cracks information (length and width), where it can be used as a speedy judgment for the deterioration-magnitude of the RC decks.

Third, the authors develop an artificial neural network model (ANN) for comprehensive judgment of the deterioration-magnitude for the crack patterns since the proposed correlation cannot evaluate the crack patterns that have the same cracks density. Bayesian regularization technique was conducted to the ANN’s training to reduce the risk of misguided ANN’s evaluation due to overlearning.

In fact, ANN is not a method to achieve physical meanings, but it may expose guidance or foresight for the unknown or future events. Then, the authors will seek for physical-structural definitions from ANN at the last of this paper. Deck’s bottom surface map for the location of the comparatively problematic cracks at the bottom surface of the RC deck is drawn, where mechanical-physical expressions are achieved from ANN’s weights.

2. Methodology for predicting the remaining fatigue life

The remaining fatigue life of the cracked RC decks can be obtained by utilizing the life-simulation based upon the multi-scale thermo-hygral analysis (Maekawa et al. 2003; Maekawa et al. 2009), and the pseudo-cracking method, where the constitutive laws are upgraded for high cycle fatigue loading (Maekawa et al. 2015, 2006; Fujiyama et al. 2010) and the concrete-water interaction (Maekawa and Fujiyama 2013; Maekawa et al. 2015) as shown in Figs. 3 and 4. Here, the coefficient of tension softening is set as 0.4 for RC-zone (Maekawa et al. 2003) and the one for the plain concrete is computed in reference to the fracture energy and the element size.

The pseudo-cracking method by Fujiyama and Maekawa (2013) is not the backward inverse analysis but the mean to seek for the invisible internal crack location, orientation and its width with regard to the visible cracking on the surfaces of RC decks. The visible surface cracks are treated as the first candidacy of data assimilated so that they may satisfy the deformational compatibility and the dynamic equilibrium, and the most probable location of internal cracking is looked for by the predictor-corrector method.

3. Artificial neural network (ANN)

Technology duplicates the operation of biological process regarding nervous by creating a mathematical struc-
ture that processes the information like biological neuron (Fausett 1994; M. I. T-Lincoln. Laboratory 1989; Grossberg 1982; Hagan et al. 1996). The core elements of the ANN are the neurons that process the information, where they are connected together by a synapse. The structure of ANN consists of the input neurons, the information processing neurons that are arranged in hidden layers, and the neurons that generate the output as shown in Fig. 5.

The structure of an artificial neuron consists of inputs, summation block, activation block and only one output as shown in Fig. 5. The neurons of different layers are connected together by synapses and each synapse is assigned with a weight which changes during the training scheme until the expected output value are achieved. The activation function is a non-linear mathematical function that processes the output of the summation block, where it provides non-linear properties of model. The role of the bias in the activation function is to enhance the shifting capabilities of the activation function to shift so it can map the inputs and the outputs easily, where the range of the activation function is generally...
(0 to 1) or (-1 to 1) depending on the used function.

The input layers receive the values of input variables. Then, the neurons of the hidden layer receive that input; process and pass it to neurons of the next layer until reaching the output layer. Then, the network compares the output value from the output layer with the actual one and the error is calculated to adjust the weights of the network. Finally, this procedure is repeated until the sum-squared errors, sum-squared weights and the effective number of parameters reach constant values.

4. Specifications for the parametric study

4.1 Description of the studied RC deck

As a reference, an RC deck under stagnant water is selected with a thickness less than 20 cm (thin decks) in consideration of current stocks of road infrastructure. Figure 6 shows the dimensions and the reinforcement arrangement of the target. Bridge decks are designed as a one-way slab supported by side girders, while its length generally depends on several conditions such as bridge types. Based on a previous research (Fathalla et al. 2018a), it was found that 6.0 m length is the optimum length to reduce simulation time and size. In fact, less difference of the fatigue life was confirmed even if the deck length is longer than 6.0 m (Fathalla et al. 2018a).

4.2 Material properties of studied RC deck as a reference

Material properties of concrete and steel of the studied deck are shown in Table 1 on the basis of general design values used in old construction of highway bridge deck (Maekawa et al. 2009).

4.3 Wheel loads of studied RC deck as a reference

Referring to the specification for highway bridges-Part III (Japan Road Association 2012), the deck is subjected to moving wheel design load of 98 kN as shown in Fig. 7. Running speed of wheel is selected as 60 km/h, which is the legal speed limit for Japanese national routes. The dimensions of the wheel are 500 and 250 mm in reference to wheel tires’ contact area.

4.4 Failure criterion

According to the past experiments and experiences, the fatigue limit state was specified based on the central live load deflection, when the one defined by Equation 1 would reach the limit state associated with no bond (Maeshima et al. 2014, see Fig. 8), it is judged as the fatigue failure. Then, the authors also accept this criterion so that the past research works can be referred. As this limit state deflection in reference to the past experiments is equal to (±3) times its initial value, the authors straightly utilize the criterion denoted by Equation 2. In fact, the deflection at the fatigue failure may

| Material Type       | Concrete | Steel |
|---------------------|----------|-------|
| Young’s Modulus N/mm² | 24,750   | 205,000 |
| Compressive Strength N/mm² | 30    | 295  |
| Tensile Strength N/mm²   | 2.2     | 295   |
| Specific Weight kN/m³     | 24      | 78    |

Table 1 Material properties of the slab for analysis.
logically depend on boundary conditions and dimensioning of specimens. But it was empirically experienced not to be beyond 3-times of the initial value. It may attribute to the fact that the fatigue rupture of reinforcement does not occur before the failure of concrete under the moving loads (Matsui et al. 1986). Thus, this criterion may safely encompass the fatigue failure of RC decks.

\[
\delta_{L,N} = \delta_{L,N} - \delta_{2,N} \\
\delta_{L,N} / \delta_{L,0} \geq 3.0
\]

(1)

(2)

where, \(\delta_{L,N}\) is central live load deflection at \(N^{th}\) of cycles, \(\delta_{1,N}\) is central total deflection at \(N^{th}\) of cycles at loading step, \(\delta_{2,N}\) is central total deflection at \(N^{th}\) of cycles at unloading step, \(\delta_{L,0}\) is initial live load deflection, \(N_f\) is the failure number of cycles corresponding to \(\delta_{L,N}\) from Equation 2.

4.5 Standardized conditions for numerical-simulation model

The analysis domain was discretized with finite elements by using the open code as FABrIS (Fujiyama et al. 2013), which is specialized for wheel running loading of RC bridge decks. Each mesh size was chosen to be 250 \(\times\) 250 mm in the X-Y plane, and the number of layers in Z-direction is four as previously validated by Fujiyama et al. (2013). The slab is supported by hinges to allow free rotation with constrained vertical displacement. As RC decks are usually connected to the top flanges of steel girders by studs and/or bolts, some moment constraint may exist. Its magnitude depends on several aspects such as twist stiffness of the girders, fastening devices in detail, etc. Then, we apply the most conservative boundary conditions so that it may give shorter fatigue life.

It should be noted that the objective and the scope of this paper are to obtain the slab’s deterioration-magnitude based up inspected crack patterns with regard to the reference case as stated previously. For the fatigue life of decks whose shapes and dimensioning differ from those of the referential case, simplified versions are being developed for further expansion of the applicable range of the proposed assessment presented in this paper.

4.6 Real crack patterns

Figure 9 shows the real crack patterns which were from the on-site investigation of 88 Japanese highway bridges’ panels. These bridge decks have almost the same dimensions and concrete properties as shown in Fig. 6 and Table 1. These crack patterns are used in the analysis of the remaining fatigue life. The crack patterns (264) with a crack width that ranges from 0.1 mm to 0.3 mm, as shown in Fig. 9, are analyzed by using the integrated system (multi-scale simulation program and PCM) to investigate the remaining fatigue life of these crack patterns (Tanaka et al. 2017; Fathalla et al. 2018). The real crack patterns will not be used in building the ANN model, but used only once at the final step to validate the ANN model.

In this study, only the bottom surface cracks are taken into account for the remaining fatigue life prediction since the top surface cracks are hard to be seen on-site due to the presence of the pavement layers. This is an engineering judgement at this moment. But, we expect in the near future that non-destructive tests (NDTs) will be used to detect unseen defects such as 3D radar system or acoustic emission (AE) tomography system, and the reliability of the assessment will be upgraded with the site crack inspection of the bottom surfaces.

5. RC decks observations and validation of multi-scale simulation

5.1 Real and experimental observations

It has been reported that by removing the asphalt layers of periodical renewal, disintegration of aggregates and cement on the deck’s top surface were found and for much severe cases, concrete almost disappeared and a hole was made in the RC deck as shown in Fig. 10. We may find those events in the region where freezing and thawing are highly repeated. The systematically arranged experimental program was conducted at Nihon University to examine RC deck performances in wet conditions under fatigue loading (Isobe et al. 2015). It was reported that the same disintegration was reproduced when the specimens were sawn as shown in Fig. 10.

5.2 Disintegration model in wet condition

The micro-fatigue model with cyclic pore pressure was integrated with the multi-scale simulation in a previous research. During the fatigue simulation of concrete composites with condensed water, the average stiffness is reduced with the disintegration of the aggregate-cement composite. The mechanism of disintegration is explained in the constitutive model as such when the micro-pressure increases; it raises the local pressure at the interface between aggregates and cement paste. This local pressure deteriorates the bond between aggregates.
and the cement paste matrix which may lead to the disintegration of the composite system (Hiratsuka and Maekawa 2015), as shown in Fig. 11.

The overall capacity of disintegrated reinforced concrete against axial compressive stress is expressed by Equation 3 (El-Kashif and Maekawa 2004), that is to say, carried by un-damaged concrete, steel and assembly of remaining aggregates after disintegration. The factor denoted by $K$ indicates the rate of erosion or disintegration. When the $(K)$ value reaches zero, it means the cement paste matrix is totally eroded and the axial compressive stress is carried only by the assembled aggregates.

$$\sigma_i = K \times \sigma_{ct} + \sqrt{K} \times \sigma_u + (1 - K) \times \sigma_{agg}$$

$$K = e^{-Z}$$

$$Z = \int_{\text{Path}} dz, \quad dZ = -10^6 \times (1 + f_n) \times P_{\text{total}} \times dp$$

Equation 3

Fig. 9 Investigated real crack patterns of RC decks in service.

Fig. 10 Disintegration under fatigue loading with stagnant water on site and laboratory tests (SIP-Program 2018).
where, \( \sigma \) is total compressive stress, \( \sigma_{ci} \) and \( \sigma_{si} \) are stresses assigned to concrete and steel, \( \sigma_{agg} \) is stress assigned to aggregate, \( Z \) is accumulated damage of concrete in micro-pore structure, \((n, f_n)\) are coefficients related to the intersection and the slope of S-N diagrams, respectively, \( P_{ampl} \) is amplitude of pore water pressure.

### 5.3 Erosion and disintegration of concrete with water

The multi-scale simulation was validated by comparing it with the observation at site and experiments. Concrete is simulated to be eroded from the upper deck’s surface at the region of loading path, which matches the reality as shown in Fig. 12. Induced cracking is represented by the multi-directional non-orthogonal smeared crack model which may cover bending cracks, inclined shear and horizontal cracking as well. In addition, higher principal strain was reproduced inside the deck in the longitudinal direction rather than the flexural and shear strains, which demonstrates the existence of inner horizontal cracks whose crack width is larger than the others.

Figure 13 shows the erosion in progress at the center of the RC deck with load cycles and the total failure at 152 thousand cycles. Figure 14 shows that pore water pressure starts to rise at the particular time when concrete is eroded.
crete is totally eroded accompanying the increase in principal strains of the top and the bottom layers. This leads to accelerated damage as shown in Figs. 15 and 16, respectively. The multi-scale simulation for disintegration of concrete decks with stagnant water are discussed and experimentally validated in more detail by Maekawa and Fujiyama (2013a, 2013b).

5.4 Dry and wet ambient conditions
The reduction in fatigue life for RC decks with stagnant water is about 1/200 in comparison with the dry case (Matsui 1987) and the simulation (see Fig. 17) reproduces the lives in dry and submerged conditions for thin (18 cm) and thick (24 cm). The simulation demonstrates that stagnant water is still serious even for the thick RC decks. The difference in the fatigue life of the thin and thick RC decks under submerged conditions is about 2.3 times, while this difference in the dry state is greatly 264 times. It means that the damage of flexural compression zone is so critical for both thin and thick slabs, and it may lead to the lost performance of the deck’s flexure. Then, RC decks suffer from total collapse. This can be clarified by monitoring the water kinetic as shown in Fig. 17. Computationally when bending compression of the concrete composite is weakened, flexural compression can only be bared by the pore water pressure. Thus, pore water pressure increases suddenly as shown in Fig. 17 for both thin and thick RC decks.

6. Massive life simulation for ANN's learning
6.1 Sound condition of the referential RC deck

Figure 18 shows the relation of the wheel load cycles and the total central deflection for the un-cracked sound case at the initial stage. According to the fatigue failure criterion mentioned in section (4.4), the fatigue life is estimated as 2.93 Million cycles. In this sound case, the live load deflection at the first cycle (A) is 1.26 mm, while the one at the failure cycle (B) is 4.55 mm. The total deflection of 5.39 mm was specified to be the failure criterion for all the studied crack cases.

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Fig. 15 Load cycles and the top principal strain of the central zone of RC deck.

Fig. 16 Load cycles and the bottom principal strain of RC deck's central zone.

Fig. 17 Dry versus wet fatigue life for thin and thick RC decks.
6.2 Cracked cases

Existing crack patterns on site have a crack width of about 0.3 - 0.4 mm as maximum within the authors’ inspection of all Japan. Firstly, the authors checked the remaining fatigue life of 264 real crack patterns with a crack width of 0.1 - 0.3 mm, as previously shown in Fig. 9, by the multi-scale simulation. Figure 19 shows the relation of the average strain (see Equation 4) and the fatigue life normalized by the sound case. Although the data is scattered, the general trend says the reduced remaining fatigue life according to the increased strains. It is also shown that the existing crack patterns on-site have fatigue lives greater than 24% of the sound case and there are no available data for higher average strain values greater than 0.1%.

These results lead us to collect further crack patterns in order to encompass all fatigue events. In order to meet this challenge, randomized artificial crack patterns program (RACP) is introduced, where it can overcome the weak points of biased training dataset. As shown in Fig. 20, RC deck must have its full fatigue life when the average strain of the bottom surface is zero, while the RC decks have no remaining life when the average strain is around 1.5% based on a previous research (Fathalla et al. 2018; Fathalla et al. 2018; Fathalla et al. 2017). The value of 1.5% is herein pointed out in considering that remaining life does not reduce linearly but it drops according to sigmoid function (see Fig. 22).

Therefore, we need large strain data like 1.5% which is larger than the prediction from Fig. 19. The range amongst these extreme boundaries is divided into numbers of divisions, where fictitious crack patterns are produced to cover all possible ranges of fatigue lives. The variation of the real crack patterns obtained from on-site is limited. Then, we decide to use the available real crack patterns only for examining the evaluation model at the final step, while the RACP will be used for building up the evaluation model by filling up the gaps of the real inspection dataset.

This is one of the points of this study. As stated previously, in the process of machine learning, unbiased training dataset shall be arranged as much as possible. Since we have no clear knowledge of crack strain and the remaining life before RACP, the authors first picked up no cracked case and sought for another extreme case of zero remaining life. Afterwards, the full range is divided into several blocks. Consequently, we may have sigmoid curve as shown in Fig. 22.

Figure 21 shows the general scheme of RACP program, where the random variables are the element number, crack orientation and crack width, where the ranges of variables are 1 - 336 (step is 1), 0 - 180 (step is 5 degree) and 0.1 - 5.0 mm (step is 0.1 mm), respectively. Two types of cracks are produced, that is, discrete and continuous. In the discrete cracks, there is no continuity between cracks of a particular element with the ones at

![Fig. 18 Load cycles versus central deflection for the initially sound case.](image)

![Fig. 19 The average strain and the remaining fatigue life for the real crack patterns.](image)

![Fig. 20 Training dataset-collecting scheme.](image)
the neighbor elements; while in the continuous cracks, there is continuity between cracks in a particular element with the ones of the neighbor elements. Based on the decided random angle in the continuous cracks by RACP, three shapes of continuity are produced: X-direction, Y-direction, or diagonal, as shown in Fig. 21.

Repetition of the crack patterns were avoided by checking the preliminary produced ones. By utilizing the RACP, 1,600 artificial random crack patterns were produced carefully to most probably cover the whole ranges of fatigue lives. Two types of crack patterns were produced as such: discrete and continuous with different length, as shown in Fig. 21. Repetition of the crack patterns were avoided by checking the preliminary produced ones.

By utilizing the RACP, 1,600 artificial random crack patterns were produced carefully to most probably cover the whole ranges of fatigue lives. Two types of crack patterns were produced as such: discrete and continuous with different length, as shown in Fig. 21. Then, their remaining fatigue life is checked by using the multiscale simulation. Figure 22 shows the relation of the average strain (see Equation 4) and the fatigue life normalized by the sound case. It was found that the fatigue life of continuous cracks is less than those of discrete cracks since the continuous cracks have more tendencies to form crack-failure path.

\[
e_{\text{avg}}(\text{A.S}) = \frac{\sum_{k=1}^{n} (\epsilon_{xx} + \epsilon_{yy})}{n}
\]

where, \(e_{\text{avg}}\) is the average strain on the bottom surface of RC deck, \(k\) is the \(k\)th element at the bottom surface of the deck, \(\epsilon_{xx}\) is the concrete’s normal strain in x-direction for the \(k\)th element, \(\epsilon_{yy}\) is the concrete’s normal strain in y-direction for the \(k\)th element, \(n\) is the total number of elements at the bottom surface of the deck.

6.3 Regression correlation

In the previous section, a clear correlation is found between the average strain of the bottom surface cracks and the remaining fatigue life. In order to simplify the calculations of the average strain parameter, another correlation is introduced between the cracks density of the bottom surface cracks (see Equation 5), by considering both cracks length and width, and the remaining fatigue life of RC decks. Figure 23 shows the relation of the cracks density and the normalized remaining fatigue. The distribution of the data is similar to the one shown in the previous section, where the average strain parameter was used. The scatter of the estimated remaining fatigue life of the discrete and continuous cracks is different, but the rate of deterioration is found to be almost the same. Thus, the \(\beta\) factor is introduced in the cracks density prediction parameter to upgrade the prediction parameter to deal with both types of cracks.

It is found that the discrete cracks have a bit longer fatigue life by 3.16 times than the one of the continuous cracks in case of the same cracks density. This differ-
ence corresponds to 2.27 times difference in the cracks density parameter. Then, the cracks density prediction parameter can be enhanced to treat the discrete cracks by decreasing their cracks density by a reduction factor \((\beta = 0.44)\). Finally, a nonlinear equation (see Equation 6) is proposed for prediction, as shown in Fig. 24, where the C.O.V of the prediction and the prediction interval (P.I) of 95% are 23.1% and 15.9%, respectively.

\[
CD = \sum_{k=1}^{K} \frac{(L_k \times W_k)}{A \times B} \times \beta
\]  

(5)

where, CD is the cracks density of the bottom surface, \(L_k\) is the length of the \(k^{th}\) crack, \(W_k\) is the width of the \(k^{th}\) crack, \(A\) is the length of the RC deck in the longitudinal direction, \(B\) is the width of the RC deck in the transverse direction, \(\beta\) is cracks type indicator; 1.0 for continuous cracks and 0.44 for discrete ones.

\[
R.L = 8.4 + 8.4 \times \tanh(-1.38 - 6.5 \times \text{CD}) \geq 0.0
\]  

(6)

where, RL is remaining fatigue life and CD is the cracks density.

### 6.4 Effect of cracks on the dry and wet conditions

The similar study was previously conducted for RC decks in a dry condition and a non-linear correlation was proposed between the cracks density and the remaining fatigue life (Fathalla et al. 2018). Figure 25 shows a comparison of RC decks in a dry with the wet condition discussed in this paper. It is shown that the effect of cracks is more significant in the wet case than the dry one due to the cracks-water interaction which was stated previously. This trend may lead engineers to pay attention to RC decks under stagnant water, where their fatigue life is reduced by \(\approx 1/100\) times comparing to the dry one. Moreover, if the bottom cracks exist, the RC deck is more deteriorated in the case of wet conditions in comparison with the sound condition.

### 7. Training artificial neural networks

To have rational time cost for the estimation of the remaining fatigue life at site, ANN is introduced on the basis of machine-learning. Here, ANN is expected to be used for massive diagnosis of bridge decks on the scheme of infra-asset management. If detailed examination is needed, the multi-scale simulation can be directly applied for more detailed life assessment for rather problematic targets.

#### 7.1 Methodology for fatigue life identification

Table 2 shows several input variables of the initial cracks on the bottom surface of the FEM model. The bottom layer was discretized into 336 finite elements in the X-Y plane in this research. In the data assimilation, each FEM element has three variables as normal strains in X-direction \((\varepsilon_{XX})\), Y-direction \((\varepsilon_{YY})\) and shear strains \((\varepsilon_{XY})\). In order to figure out the best performance variables for building the ANN model, a comparison of the prediction accuracy of the ANN results has been made of five sets of variables as shown in Table 2. For cases
The number of elements of the deck’s bottom surface is reduced from 336 elements (see Fig. 26) to 84 elements (see Fig. 27). The cracks’ information for the cases (3 ~ 5) is taken as a sum for each 500 × 500 mm² area instead of 250 × 250 mm² of the deck’s bottom surface.

In case (5), only principal strain is considered, while the information of cracks’ direction is lost. It should be noted that cases (1, 3) and cases (2, 4) have the same physical-mechanistic meanings since in the pseudocracking method (Fujiyama et al. 2013), the space-averaged strains are calculated based on the local coordinates whose axis is parallel to the crack direction, where shear and normal strains along the crack are assumed to be zero. Then, the local strain tensors are converted to global coordinates as three in-plane tensors, but one constraint exists; the second principal strain always becomes zero. Here, the three independent variables for the cracks are mechanically reduced to only two independent variables. In cases (2, 4), the principal strain and its directional angle are used instead of the strain tensors according to equations (7 - 8). This ex-

Table 2: Four sets of ANN’s input variables.

| Case No. | Variables for Each FEM element | No. of Elements | Total number of variables | Cracks Direction |
|----------|--------------------------------|----------------|--------------------------|------------------|
| Case (1) | ε_xx, ε_yy, ε_xy             | 336            | 1008                     | Included “Indirectly” |
| Case (2) | ε_1, θ (Equations 7 & 8)     | 336            | 672                      | Included “Directly”  |
| Case (3) | ε_xx, ε_yy, ε_xy             | 84             | 252                      | Included “Indirectly” |
| Case (4) | ε_1, θ (Equations 7 & 8)     | 84             | 168                      | Included “Directly”  |
| Case (5) | ε_1                           | 84             | 84                       | Not included       |

Fig. 26 Input and output variables in ANN fatigue life problem for cases (1) & (2).

Fig. 27 Input and output variables in ANN fatigue life problem for cases (3), (4) and (5).
pression is easier to understand the characteristics of crack for human sense. When multiple cracks are induced in the element, only principal crack is considered in machine learning process in cases (2, 4) while secondary crack is also taken into account in cases (1, 3). Here, it should be noted that large number of neurons and layers do not necessarily lead to the better ANN model.

\[
\varepsilon_i = \frac{\varepsilon_{xx} + \varepsilon_{yy}}{2} + \sqrt{\left(\frac{\varepsilon_{xx} - \varepsilon_{yy}}{2}\right)^2 + \varepsilon_{yx}^2}
\]

(7)

\[
\theta = 0.5 \times \tan^{-1}\left(\frac{2\varepsilon_{xy}}{\varepsilon_{xx} + \varepsilon_{yy}}\right) \times \frac{180}{\pi}
\]

(8)

where, \(\varepsilon_1\) is the maximum principal strain, \(\theta\) is its principal directional angle (degrees), \(\varepsilon_{ij}\) is the strain tensors of concrete on the bottom surface of the RC deck.

The dataset for training and validating ANN is supplied by the multi-scale simulation, and they are the input of the machine-learning block. The training data is used to adapt the weights of the ANN, and the test dataset is used at the final step after the model is built to examine the versatility of the built ANN. After training with the dataset in the machine-learning block, if the ANN can correctly map the training data and identify the testing data with good accuracy, it is considered as a trained ANN. Finally, the remaining fatigue life can be obtained for any crack pattern in seconds without the need for running multi-scale simulation programs.

7.2 Requirements of ANN’s training dataset

The quality of the training dataset for ANN is an essential matter. It should be chosen attentively to cover all possible events. Once one of the events is not provided to the training dataset, the accuracy of prediction of the model regarding that event is totally lost. According to the laws of symmetry, the mirror crack patterns should logically have the remaining fatigue life of the original crack patterns. Therefore, they should be included in the dataset of the ANN. The two symmetric lines in the longitudinal and transverse directions were taken into consideration, as shown in Fig. 28.

In the normal conditions, the crack patterns in the real case have a crack width of a maximum value of 0.3 - 0.4 mm, but the authors intentionally introduce higher crack width up to 5.0 mm. Also as stated previously, ANN model will be built based on artificial crack patterns. The reason for these decisions is to secure the robustness of the prediction of any unexpected events regarding extraordinary crack patterns or larger width that may happen in future and to extend the applicable range of the predictive model.

7.3 Neural network platform and structure

The platform used to build ANN is MATLAB R2017a-Neural Networks Toolbox. Uni-directional feedforward network and Bayesian regularization training function were utilized for building the ANN (Hagan et al. 1996; Murphy 2012; Hagan and Menhaj 1994; Rumelhart et al. 1986, Burden and Winkler 2008; Foresee and Hagan 1997; MacKay 1992). Bayesian regularization neural networks (BRANN) in many cases are robust to avoid overfitting since it uses L2 regularization, and therefore is expected to generalize well (MacKay 1992). The structure of the built ANNs is as shown in Table 3. The number of hidden layers and neurons are optimized through trial and error procedure. Even though the number of layer and neuron is unity, it is still ANN because the neuron is directly connected to every data with nonlinear function. This complexity is more than the case of statistical models.

### Table 3 ANN’s structure.

| Case No. | Number of hidden layers | Number of neurons | Data format |
|----------|-------------------------|-------------------|-------------|
| Case 1   | 1                       | 1                 | Strain tensors |
| Case 2   | 1                       | 1                 | Principal strain & directional angle |
| Case 3   | 1                       | 2                 | Strain tensors |
| Case 4   | 1                       | 2                 | Principal strain & directional angle |
| Case 5   | 1                       | 2                 | Principal strain |

Fig. 28 Mirror crack patterns.
of the validation subsets are statistically obtained as shown in Fig. 29. On the basis of cross-validation results as shown in Fig. 30, it is found that the principal strain magnitude and its direction (cases 2, 4) are more robust in training ANN’s dataset than the strains tensorial expression (cases 1, 3) in spite of the fact that they both have the same physical-mechanistic meaning in the scheme of the pseudo cracking method (Fujiyama et al. 2013). Thus, it can be said that selection of the best-input variables is a crucial point to obtain ANN model with high performances. Figure 29 shows the results of the cross-validation of the best-input variables (case 4), where the decision coefficient is 0.94, prediction interval of 95% (P.I) is 0.16, and the mean square errors (mse) is 0.0069. By introducing ANN, the prediction accuracy is enhanced, where the mean square errors (mse) is reduced from a value of 0.0164 to 0.0069 compared to the proposed equation as the regression line in Fig. 22, as shown in Fig. 30.

At present, during the assessment of the damage of RC decks from the inspected bottom surface cracks, we generally focus on the cracks density and the crack width data at site. In normal cases, much attention has never been directed to the cracks orientation. Cross-validation’s accuracy is upgraded by including the cracks orientation, where the mean square error is reduced from a value of 0.0098 to a value of 0.0069, as shown in Fig. 30. Thus, the cracks orientation is demonstrated to be an important factor for enhancing the prediction accuracy of the remaining fatigue life of the RC decks.

In order to evaluate how large the difference is in view of the bridge engineering, load-life diagram (S-N diagram) is drawn by the multi-scale simulation for the referential RC deck as shown in Fig. 31. The prediction interval of variance of 95% of the cross-validation (see Fig. 29) is (± 16%). It corresponds to just (± 3.9%) difference in load levels because of the logarithmic scale. The small variation in terms of the load magnitude attributes to its great sensitivity to life. This is almost the limit prediction and reproducibility of structural ex-

![Fig. 29 Relation of the calculated fatigue life by simulation program and the one by ANN for the cross-validation results of case (4).](image1)

![Fig. 30 Leave-one-out cross-validation results for different input variables.](image2)

![Fig. 31 S-N diagram for the referential RC deck.](image3)
eriments in laboratories.

It can be said again that the accuracy of built ANN depends on both the number of data and the number of neurons. As many neurons require heavier learning with large amount of dataset, unnecessary layers and/or neurons can make ANN poor with limited number of data.

7.5 ANN generalization evaluation of the chosen ANN model

As the ANN model of the case (4) shows the highest performance, it is chosen most probably as the candidate. Mirror crack patterns in both transverse and longitudinal directions are included in the training dataset (1600 × 4 = 6400 data) for the proposed model as discussed in section (7.2). The mean square errors, the performance gradient and an effective parameter of BRANN reach stable states as shown in Fig. 32. If the training parameters for BRANN reach stability, we have the convergence of solution. Then, let us examine the network with real crack patterns besides their mirror cases (264 × 4 = 1056 data) in terms of the robustness against independent unknown data. Figure 33 shows the relation of the fatigue life obtained from the multi-scale simulation and the estimated fatigue life from the proposed ANN model of the real crack patterns. The distribution of the test data around the best-fit line (ideal mapping) is small with a C.O.V of 12.1%. The prediction accuracy toward unknown data demonstrates the reliability of the proposed ANN model.

7.6 Structural mechanistic expressions of ANN’s weights

Although ANN is not a method to clarify the mechanistic rationale, it may expose guidance or foresight for the unknown or future events. We may utilize AI not only for developing predictive tools, but also to get a physical correlation and/or “unified experience” that may help in a better engineering understanding of a target problem. Then, the weights assigned with the synapses of the neuron are assigned to each crack location to achieve a map of the problematic cracks and to link these results with the structural knowledge for validation.

An ANN is built with the same input variables and training function (BRANN) of the case (5). The network’s structure is one hidden layer with one neuron. Only the crack magnitude is taken into account to show the cracks’ location impact. The training dataset includes 1,600 RACPs and 264 real crack patterns besides their mirror crack ones. Equation 9 shows the correlation of the ANN model which was built with principal strains. Figure 34 shows the relation of the damage index (see Equation 10) and the normalized fatigue life, where the remaining fatigue life decreases when the
The ANN maps the training dataset with a good accuracy, where the prediction interval of variance of 95% has a value of 14.4%.

\[ R.L = 1.3 - 1.3 \times \tanh(0.24 \times [S]_{484} \times [W]_{4841}) \] (9)

\[ \text{Damage Index} = [S]_{484} \times [W]_{4841} \] (10)

where, R.L is the remaining fatigue life, [S] is the input vector for the principal strains of the FEM elements (84 elements), [W] is the trained ANN’s weight vector (known values).

First, size of the networks as listed in Table 3 was chosen based on the optimum size of networks to avoid overfitting. Second, it was found for the case (5) that the one hidden layer with two neurons has the best performance. But, in order to develop hazard map for the location of cracking on the basis of weights assigned with the synapses of the neurons, one neuron was chosen for a clear understanding of the weights. As the prediction of the ANNs of the case (5) has almost the same accuracy, the biases of the network is only constant and the size of matrix of the weights gets 84 × 1.

The weights of the connections from the inputs to the neuron (synapses) are thought to represent how large the impact of cracks location is. Figure 35 shows the contour of weights distribution, normalized between 0 and 1 of the discretized RC deck’s bottom surface (84 elements). The map shows the ANN model has learned the law of symmetry in both directions, where full symmetry is obtained. It is also found that the corners of the RC deck are the key locations to be focused at visual site inspection. It should be noted that the ANN pays its attention to cracks nearby corners before failure so as to judge the final failure when shear cracks may arise more close to the loading lanes.

The key locations of cracks obtained from the ANN can be discussed from a structural view point. It is well known that the corners of the RC deck have the maximum shear force based on the structural analysis of the slabs. Thus, the existence of pre-cracks at the corners might be a witness of diagonal shear cracks. As a matter of fact, it was reported that the excessive deflection of underground culvert’s top slabs is caused by the occurrence of out-of-plane diagonal shear cracks at the corners (Maekawa et al. 2016). In contrast, cracks at the loading path area do not play a major role in the reduced fatigue life because it is almost deteriorated by the pumping pressure from the wheel loading cycles, where disintegration happens between the cement paste and the aggregates at the loading path area.

A comparison has been done between two crack patterns with the same cracks density (0.4 mm crack width) but different cracks locations as shown in Fig. 36. It is clear that the difference of these fatigue lives of two cases by utilizing ANN model by Equation 9 is around 1.45 times aiming to the cracks location effect on the remaining fatigue life, where the proposed hazard map is clarified. The correlation by Equation 6 cannot fully capture this difference due to the lack of information of the cracks density parameter.

8. Conclusions

Two evaluation methods, which were efficiently built based upon the integrated lifetime simulation system (multi-scale simulation program & pseudo-cracking method), are proposed for the practical deterioration-magnitude assessment of in-service RC bridge decks under stagnant water. The proposed correlation aims to a speedy judgment of the deterioration-magnitude of the RC decks according to the site inspection data of cracks, while the ANN model aims to a comprehensive judgment of deterioration-magnitude of the RC decks. Based on the simulation results and the proposed assessment methods, the following conclusions are drawn.

1. The evaluation methods offer a quick quantitative assessment for remaining fatigue of in-situ RC bridge road decks in service based on their bottom surface cracks. Thus, a reliable maintenance plan of RC decks can be achieved by knowing the remaining life quantitatively without running the 3D
2. It is quantitatively proved by investigating introduced cracking damages of the wide variety that the crack orientation and their patterns over the bottom surfaces of RC decks play a critical role for the fatigue life assessment as well as crack widths.

3. The proposed correlation on the basis of the mechanical parameter (cracks density) provides a simple equation with fair accuracy for deterioration-magnitude evaluation of the RC decks based on the bottom surface cracks, which fulfills the needs of engineering practice and design codes.

4. Using Bayesian regularization training rule and testing the model among unique independent real crack patterns secure the robustness and the generalization of the proposed ANN model.

5. It has been demonstrated that the stability of RC decks under stagnant water is governed by the disintegration phenomena more than the global stiffness of the RC deck.

6. The simulation results show that the effect of the cracks on the RC decks in wet conditions is more significant than the dry one.

7. Deck’s bottom surface map for the locations of comparatively problematic cracks is created, and it is found that RC deck’s corners are the key locations which have much to do with the remaining fatigue life.

8. It is demonstrated that artificial intelligence is not just a tool for creating predictive models, but it can guide somehow to achieve physical-mechanistic expressions for a particular problem.

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