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APPLICATION OF 3D-RBSM INTEGRATED WITH MACHINE LEARNING TO ESTIMATE RC CORROSION DISTRIBUTION FROM SURFACE CRACKS

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Key words: Corrosion estimation, cracking reproduction, Rigid body spring model, Machine learning

Abstract: Understanding the degree of reinforcing bar corrosion in reinforced concrete (RC) structures is crucial for evaluating the behavior. This study develops a simulation system for estimating the corrosion distribution along the rebar of a RC beam member based on surface crack widths. The system integrates the rigid body spring model (RBSM) with machine learning methods. The RC beam is modeled and RBSM simulations with different expansion distributions are run with 500 analysis steps. The expansion data and the corresponding surface crack width data generated from the simulations are used to build the training dataset for machine learning. A large number of training data samples are obtained by extracting the simulation results step-by-step. The inputs are surface crack widths from several locations and the desired output is the internal corrosion-induced expansion. After training with the dataset, the neural network is able to correlate inputs and outputs, allowing it to estimate an expansion distribution from given cracking data. The estimated expansion distribution is then used to simulate the surface cracks using RBSM, and the error between the given cracking data and simulated cracks is returned as an input to the trained network in order to optimize the expansion estimation and enhance performance of the system. The feasibility of the proposed RBSM-neural network system is validated using both synthetic and experimental test data. The estimation results align well with the target data, demonstrating the effectiveness of the system in estimating internal expansion along the rebar and reproducing the cracking distribution using surface crack data. Internal distributions of cracking and stress states are extracted from the simulations, providing additional information for further analysis of structural performance.

1 INTRODUCTION

In RC structures exposed to chloride-rich environment, corrosion is a significant cause of structural deterioration [1]. Corrosion initiates at the steel-concrete interface, and expansion pressure is caused by the rust, leading to cracking at the surface eventually. The residual performance of corroded structure is strongly affected by the corrosion degree [2], and the knowledge of corrosion state is crucial for maintenance. Some nondestructive approaches have been used to examine the internal corrosion condition, such as the half-cell potential method [3] and the polarization resistance method [4]. However, these methods are not able to provide an accurate estimation of the corrosion distribution. Numerical simulations can be used to analyze the structural performance of corroded RC members by modelling the rebar corrosion and reproducing observed cracks. Finite element method (FEM) [5] and discrete analysis method such as RBSM [6] have been used for the purpose. Surface cracks can serve as indicator for assessing corrosion level, and previous researches [7,8] have developed a system by integrating model predictive control (MPC) with RBSM to estimate inner corrosion based on observed cracking. The results are close to the target with acceptable variation, while an alternative evaluation method with higher accuracy is desired. Machine learning has been widely used in inverse analysis to predict outputs based on input data. Such an approach is suitable for estimating internal corrosion distribution given the input surface crack width data. The multilayer perceptron (MLP) network is applicable for analyzing nonlinear relationship between inputs and outputs as a typical type of neural network [9]. This study aims to develop a machine learning-based method for internal corrosion estimation (output) given surface crack width data (input). The cracking distribution is then reproduced using the estimated corrosion distribution. The RBSM-neural network system is proposed by integrating MLP network with RBSM. The network is trained with the training dataset created by RBSM simulations, and then used for estimating internal corrosion from given surface cracking data. The estimated corrosion is used to run an RBSM simulation, and the simulated cracking is compared with the target cracking. An optimization process is conducted until the results reach satisfactory accuracy. The predicted results verify the capability of the RBSM-neural network for estimating internal corrosion distribution and reproducing matching surface cracking distribution.

2 NUMERICAL MODEL

2.1 Rigid body spring model (RBSM)

The RBSM was proposed by Kawai et al. [10] and the 3D version was further developed by Nagai et al. [11,12]. This model treats the simulation object as rigid bodies, and the adjacent elements are connected with three springs (1 normal spring and 2 shear springs) as illustrated in Figure 1. Each element has 6 degrees of freedom (DOF) and the spring response represents the interaction between the elements. The elements are randomly meshed using the Voronoi diagram as Figure 2 shows.

The constitutive models in Figure 3 [13] are adopted to determine the normal and shear spring properties between the concrete elements. Cracking occurs when the normal spring stress exceeds the material tensile strength, as Figure 3a shows. Shear spring is assumed to be elasto-plastic as illustrated in Figure 3b, with the maximum shear stress calculated by Eq. 1 shown in Figure 3c. Figure 3d shows the stress-strain relationship for the normal spring between the rebar elements represented by Eq. 2, while the shear spring is assumed to behave elastically. At the steel-concrete interface, the normal and shear springs follow the same constitutive law as the springs between the concrete elements, while the tensile strength is reduced by half according to previous studies [14].

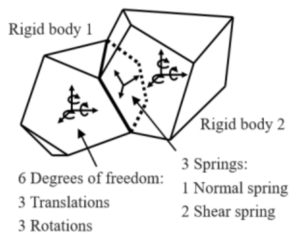


Figure 1: Rigid bodies in RBSM

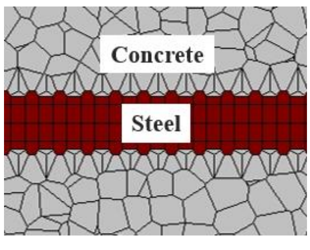
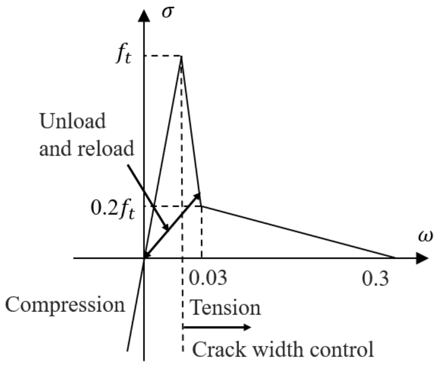
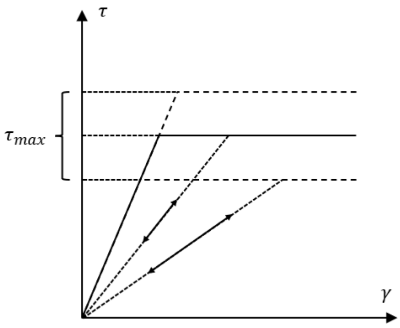


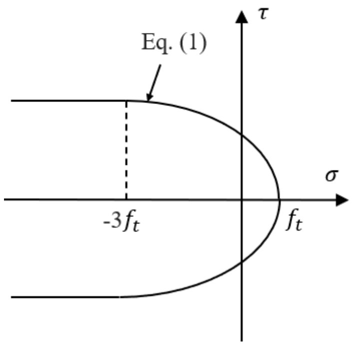
Figure 2: Concrete and steel mesh



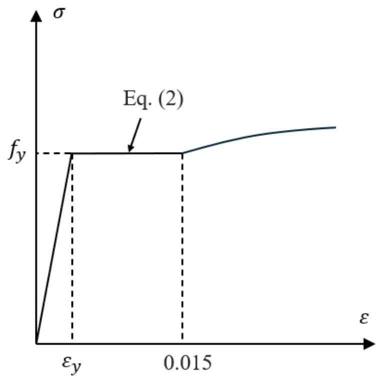
(a) Normal spring for concrete



(b) Shear spring for concrete



(c) τ_{max} criteria for concrete



(d) Normal spring for steel

$$\tau_{max} = \pm(1.6f_t{}^2(-\sigma + f_t)^{0.4} + 0.15f_t) \quad \text{for } -3f_t \le \sigma \le f_t$$
$$\tau_{max} = \pm(1.6f_t{}^2(4f_t)^{0.4} + 0.15f_t) \quad \text{for } \sigma \le -3f_t \qquad \text{Eq. (1)}$$

$$\sigma_s = E_s\varepsilon \quad \text{for } \varepsilon \le \varepsilon_y$$
$$\sigma_s = f_y \quad \text{for } \varepsilon_y \le \varepsilon \le \varepsilon_{sh} \qquad \text{Eq. (2)}$$
$$\sigma_s = f_y + (1 - e^{\frac{\varepsilon_{sh}-\varepsilon}{k}})(1.01f_u - f_y) \quad \text{for } \varepsilon_{sh} \le \varepsilon$$

σ – stress of normal spring (MPa)
τ – stress of shear spring (MPa)
ε – strain of normal spring
γ – strain of shear spring
ε_y – yield strain of steel
ε_{sh} – initial strain hardening, assumed to be 1.5%
f_y – yield strength of steel (MPa)
f_u – ultimate strength of steel (MPa)
f_t – tensile strength of concrete (MPa)
τ_{max} – maximum shear stress (MPa)
ω – crack width (mm)
k – $0.032 \times \left(\frac{400}{f_y}\right)^{\frac{1}{3}}$

Figure 3: Constitutive models of springs [13]

2.2 Corrosion expansive model (CEM)

The corrosion product (rust) generates radial stress which leads to surface cracking. The effect of corrosion can be replicated by introducing incremental expansion at the steel-concrete interface proposed by Coronelli et al. [15] and Lundgren et al. [16]. In corrosion expansive model (CEM), the expansive strain is added to the springs to simulate the rust accumulation as Figure 4 shows. The corrosion in real cases has a non-uniform circumferential distribution, while a simplified uniform distribution is assumed in this study. Jiradilok et al. [6,14] and Kumar et al [17] have confirmed the validity of the model by generating reasonable cracking behavior and proper structural performance evaluation.

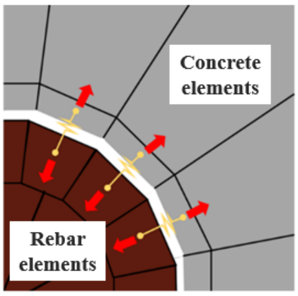


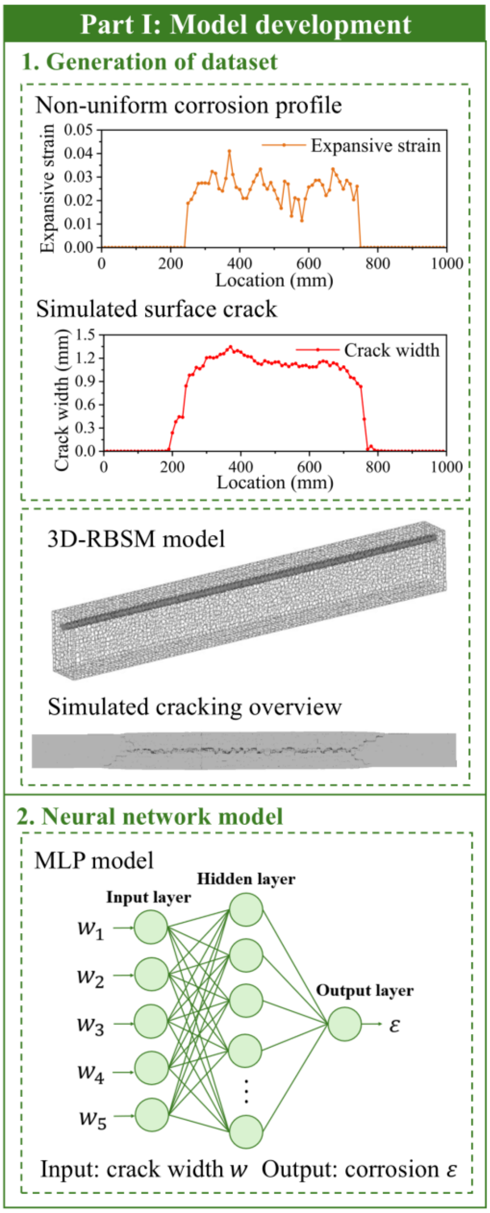
Figure 4: Interface expansive strain

3 FRAMEWORK OF RBSM-NEURAL NETWORK SYSTEM

Since the surface cracking is the available data in most cases, a method for estimating the inner corrosion from the observed crack data is desired. A machine learning method is suitable for building a relationship between the measured crack and corresponding expansive strain.

Figure 5 illustrates the framework of the proposed RBSM-neural network system. In part I, the training dataset for the network is built. Reinforced concrete structure models are created and different expansion distributions are added to the steel-concrete interface. The corrosion-induced surface crackings associated with the input expansion are recorded and used for constructing training dataset, as shown in Step 1. The MLP model builds connections between input crack width and output corrosion as Step 2 shows.

In part II, the estimation is conducted with the trained network. The target surface crack distribution is first input to the network, yielding the expansion estimation (Step 3). An RBSM simulation is run using the expansion to evaluate the estimation, and the simulated cracking is compared with the target cracking (Step 4). The cracking difference is extracted



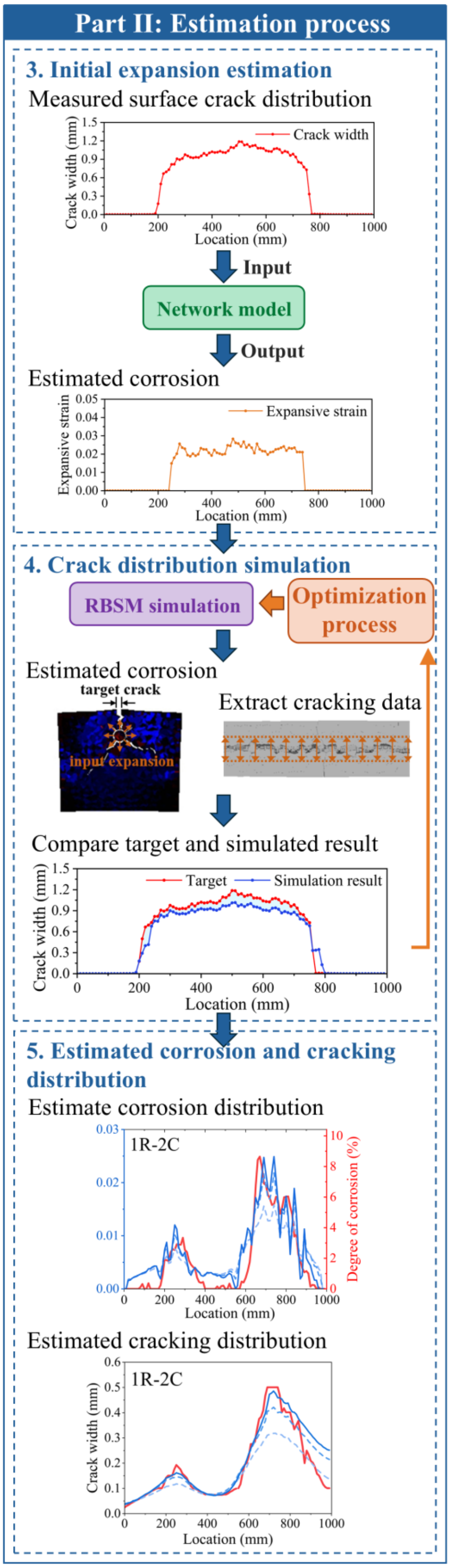


Figure 5: Framework of RBSM-neural network system

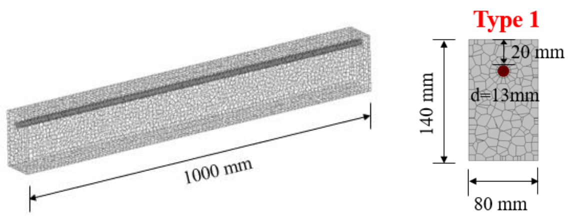
and input to the network, resulting in expansion difference as output, which updates the expansion results as an optimization process. The process is repeated until the error is acceptable, and the updated expansion and simulated cracking are the final output (Step 5).

4 NEURAL NETWORK TRAINING

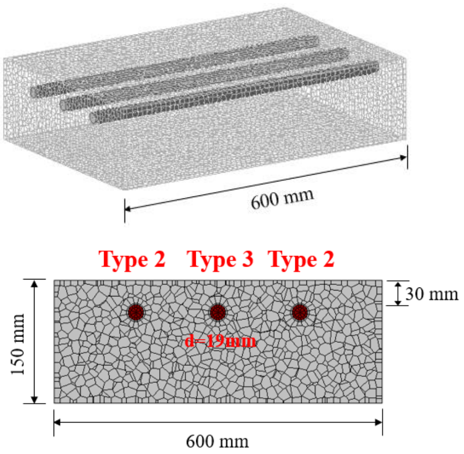
4.1 Training database

A large amount of data samples is required for the network to be well-trained and make accurate predictions. The model used for building training dataset is a reinforced concrete beam with a single rebar or three rebars as shown in Figure 6. The rebars are categorized into three types, representing different location properties. Type I is the single rebar case, type II corresponds to that corrosion occurs in the two side rebars in multiple rebar cases, and type III represents that corrosion occurs in the rebar between other rebars. The material properties of steel and concrete used for the model are shown in Table 1. The beam is longitudinally divided into several elements with a mesh size of 10 mm, and the crack width data is obtained as the relative displacement between the elements at the surface with an interval of 10 mm. Gauge length between the elements is 40 mm. Figure 7 shows the crack measurement of type I case, with the data in the range of half its length at the middle part selected for training.

In order to build the training dataset, 16 simulation cases are run for type I, and 15 simulation cases are run for type II and type III. Several randomly or regularly distributed expansions are added using CEM, and the simulations are run for 500 steps. The crack width data and input expansion are recorded at every step. An example of the simulation data at every 100 steps is shown in Figure 8.



(a) Overview and cross section of specimen for type I case



(b) Overview and cross section of specimen for type II and type III cases

Figure 6: Simulation model

Table 1: Material properties of the model

	Elastic modulus (GPa)	Yield strength (MPa)	Tensile/Ultimate strength (MPa)
Concrete	35	/	3.0
Steel	200	450	700

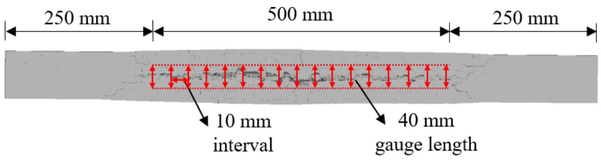


Figure 7: Cracking measurement of type I case

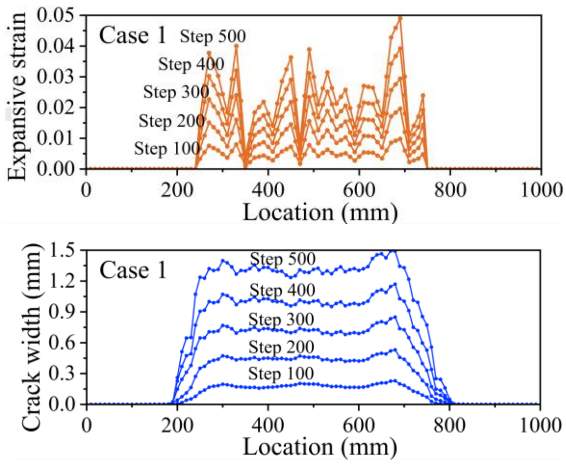
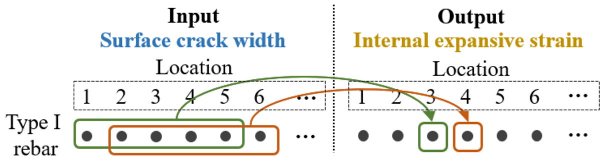


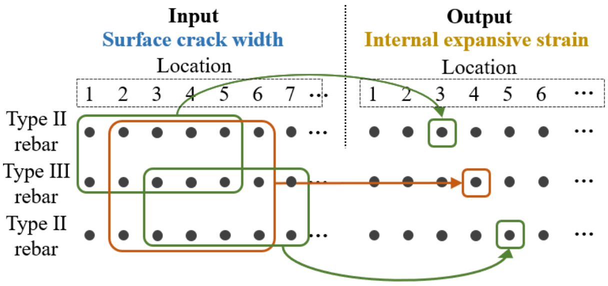
Figure 8: Simulation case for training (type I)

4.2 Network structure

The MLP network is trained with sufficient training dataset. As shown in Figure 9, for type I case, the inputs are the surface crack width data at the target location together with the data from four adjacent locations, and the output is the inner expansion at the target location. For type II and type III cases, the inputs are the crack width at five locations of the target rebar and the neighboring rebar. All data along the rebars are used for training. The influence of the neighboring locations is taken into consideration, and the number of training data samples for the three types of cases is 368,000, 420,000 and 210,000, respectively.



(a) Data structure of type I case



(b) Data structure of type II and type III cases

Figure 9: Data structure of MLP network

5 VALIDATION OF RBSM-NEURAL NETWORK SYSTEM

5.1 Results of type I case

The feasibility of the proposed system to make estimations on type I case is verified through experimental data performed by Kuntal et al. [8]. Figure 10 illustrates the dimensions of the experiment specimen, and the accelerated corrosion test is conducted as Figure 11 shows. The degree of corrosion is defined based on the reduction of cross section area. The simulation model is built with the same dimensions as the experimental specimen, and the material properties for the model elements are presented in Table 2.

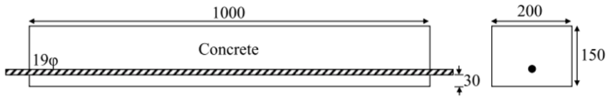


Figure 10: Dimensions of experiment specimen [8]

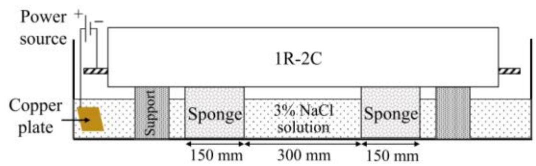


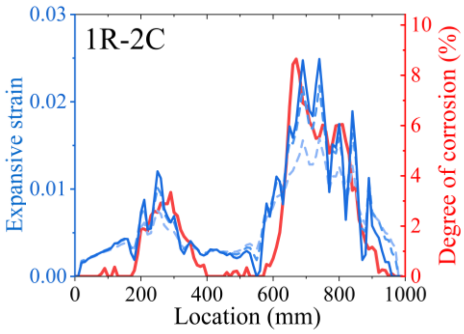
Figure 11: Accelerated corrosion test setup [8]

Table 2: Material properties of simulation model

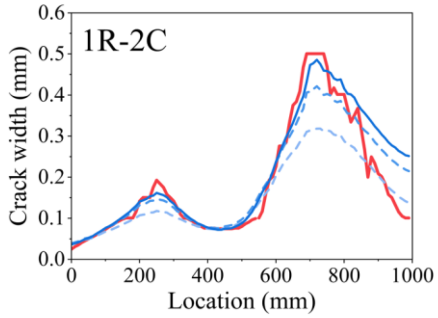
	Elastic modulus (GPa)	Yield strength (MPa)	Tensile/Ultimate strength (MPa)
Concrete	33	/	3.0
Steel	196	400	620

The estimated expansion and reproduced cracking distribution with two optimization iterations are shown in Figure 12. To compare the estimated expansion from RBSM-neural network with the degree of corrosion in experiment, a coefficient η proposed by Kuntal et al. [8] is adopted. By multiplying with η, the expansion value is converted to the degree of corrosion, while the value of η is determined by matching the peak value of estimated expansion and target degree of corrosion. From the results, it can be observed that the estimation improves with the iterative optimization. The estimated corrosion aligns well with the target experimental value. For the cracking reproduction, in spite of the small deviation at the right end, the simulated cracking distribution is in good agreement with the experimental results.

Figure 13 compares the experimental cracking pattern with the simulation, and the results are similar. The internal stress and internal crack distribution can also be extracted as illustrated in Figure 14. The 3D-RBSM simulation generates reasonable inner conditions at each step, which can be used for structural performance analysis and future state prediction.



(a) Corrosion estimation



(b) Cracking reproduction

Target 0 iteration 1 iteration 2 iterations

Figure 12: Comparison between predicted and experimental results

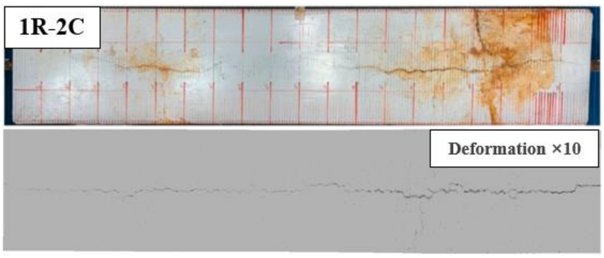


Figure 13: Experimental and simulated surface crack

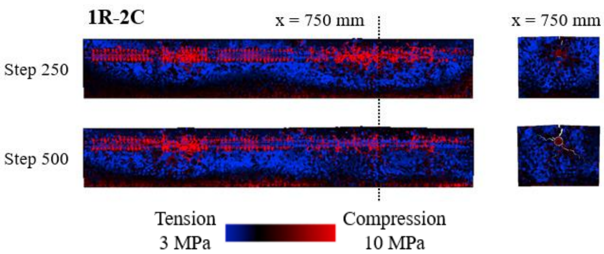


Figure 14: Internal cracking and stress distribution

5.2 Results of type II and type III cases

The feasibility of the proposed method on multiple rebar case is verified using synthetic test data with regularly distributed expansion. The data is generated from RBSM simulation with the same model configuration in Figure 6b. The expansion estimation and cracking reproduction results of two test cases are shown in Figure 15. From the results, it can be seen that the overall trend of estimated expansion and cracking distribution is close to the target, and the optimization process is not conducted since the results are already acceptable. By inputting the crack width data from neighboring rebars, the network takes the influence of the data from surrounding locations into consideration when making predictions.

The results indicate that the RBSM-neural network system provides good estimations on internal expansive strain and cracking distribution of RC structures with multiple rebars, demonstrating the potential of the proposed method to make predictions using two-dimensional input and output data. The system can be applied to more complicated cases, such as simulations with randomly distributed expansion and experimental cases, to investigate its effectiveness.

6 CONCLUSION

In this study, a new approach for estimating the internal corrosion distribution of RC members given the observed surface crack data is proposed. This method is an integration of RBSM and machine learning, and the performance of the developed system is evaluated with experimental and synthetic data. The following conclusions can be drawn from this work:

1. The RBSM-neural network system can effectively estimate internal corrosion and simulate surface cracking distribution of RC beam using experimental data for single rebar case (type I). The simulation can generate accurate results after the optimization iteration.
2. For single rebar case (type I), the surface cracking pattern obtained from simulation is similar to the experimental results. The internal stress and cracking distribution can be extracted with the simulation, which can be applied to analyze structural performance.

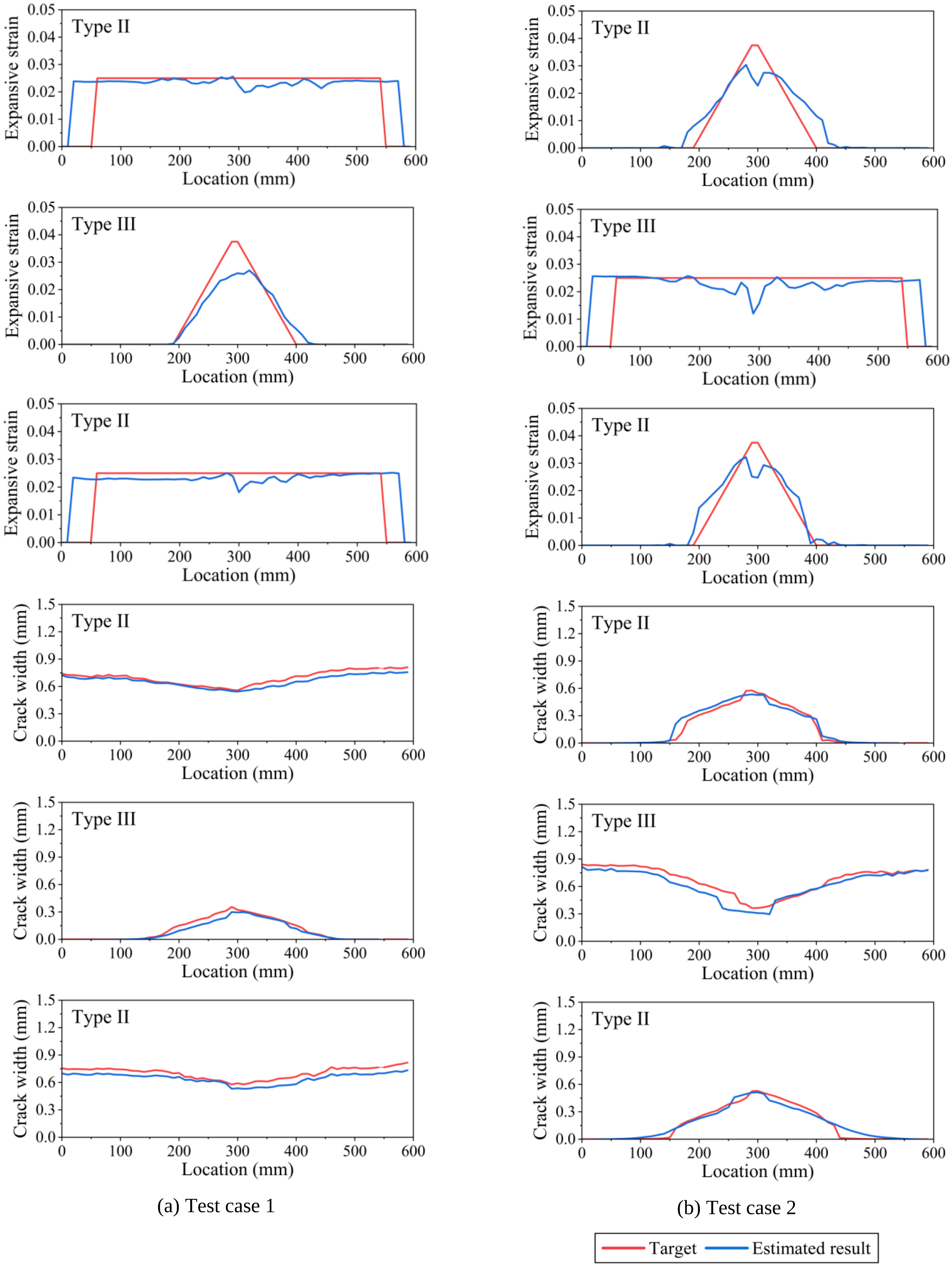


Figure 15: Estimated expansion and cracking distributions

3. For multiple rebar (type II and type III) cases, the estimated expansion and cracking distribution match the target in general. The applicability of the system on RC structures with multiple rebars can be further studied using experimental data.
4. The RBSM neural network can take the influence of crack width data from neighboring locations of single rebar case into account when making estimations. For multiple rebar cases, the cracking data from neighboring rebars are also considered, which increases the accuracy of the prediction.

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