공학석사 학위논문

Application of Recurrent Neural Network to Prediction of Structural Deterioration

구조물 노후화 예측을 위한 순환신경망 방법론의 적용

2018 년 2 월

서울대학교 대학원

건설환경공학부

최 수 빈

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이 논문을 공학석사 학위논문으로 제출함
2018 년 2 월

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최수빈의 공학석사 학위논문을 인준함
2018 년 2 월

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Abstract

Degradation and obsolescence of structures shows limitations to preemptive forecasting and corresponding response because of various uncertainties. In order to overcome this challenge, this study proposes a methodology for combining Structural Health Monitoring (SHM) data obtained during operation, which is one of the deep learning algorithms, and deterioration progress models based on mechanistic knowledge by using Recurrent Neural Network (RNN). Recurrent neural network is one kind of deep learning methodology used to learn the input data accepted in time order, and it is currently actively applied the areas of language awareness and modelling. Accurate prediction and evaluation of the aging of the structure can be possible by recursively updating the monitoring data through the recurrent neural network. Accurate prediction and evaluation of a structure's obsolescence can be achieved by updating it recursively with monitoring data via a recurrent neural network. It can be confirmed by comparing with the results of the existing aging prediction model and additionally the accuracy of the recurrent neural network model is determined by checking the results regarding to the number of base training data sets. It also verifies its performance and enables better forecasting by proposing new algorithms that can be applied to the obsolescence of structures as well as applying existing recurrent neural network.

Keywords : Recurrent Neural Network, Machine Learning, Structural Deterioration and Obsolescence, Decision Making.

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Chapter 1. Introduction

1.1. Objectives, Framework and Importance of the Research

The damage and collapse of structures due to obsolescence is very difficult to predict and also prevent because the uncertainties are very high due to the combination of various causes. In particular, as the number of obsolescence structures increases so that the collapse accidents increase, more sophisticated structural performance prediction techniques are required to reduce the damage and to promote sustainable social development. Figure 1 shows the image of collapse caused by an obsoleted structure. Recently effective methodologies are being developed to combine health monitoring data with epidemiological degradation models during the operation of structures. This study proposes a new framework different from the existing methodology using the recurrent neural network. If it is applied, it is expected that quantitative reasoning and prediction of the degree of future obsolescence will be possible from indirect data such as displacement and strain of the measured structure, also it can be utilized for various decision making on the usability of the structure.

Figure 1 Image of collapse caused by an obsoleted structure

1.2. Study Background

According to the Korea Facility Safety Agency, the percentage of obsolete infrastructure over 30 years is expected to reach 33.7% in 2029. Figure 2 shows the change in the percentage of obsoleted structures over time in Korea. In order to set up an optimized structural maintenance plan or to reduce its cost, the obsolescence of the structure should be properly predictable as the number of obsolete facilities increases. However, it is difficult to predict the process and pattern which it appears since obsolescence implies uncertainty and complexity.

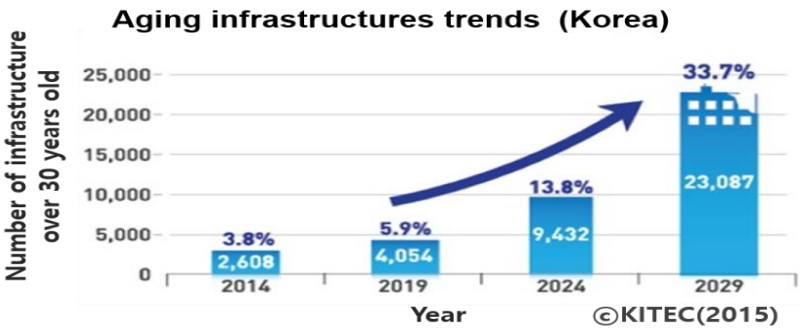

Figure2 Graph about estimated percentage of obsoleted structure in Korea by 2029

So far, obsolescence patterns of structures have been predicted through monitoring data, observational data and obsolescence progress models. But problems have emerged with the incorrectness of this obsolescence model and its application in new circumstances.

So as an alternative to this problem, one of the bayesian filters, a particle filter was introduced. The particle filter is one kind of the bayesian filter. Also, as a model-based methodology, adjust the parameters of the model through monitoring data assuming that the obsolescence model is already know. Figure 3 shows the bayesian filter algorithm for detecting obsolescence.

Bayesian Filter (Yamashita & Murakami, 2000)

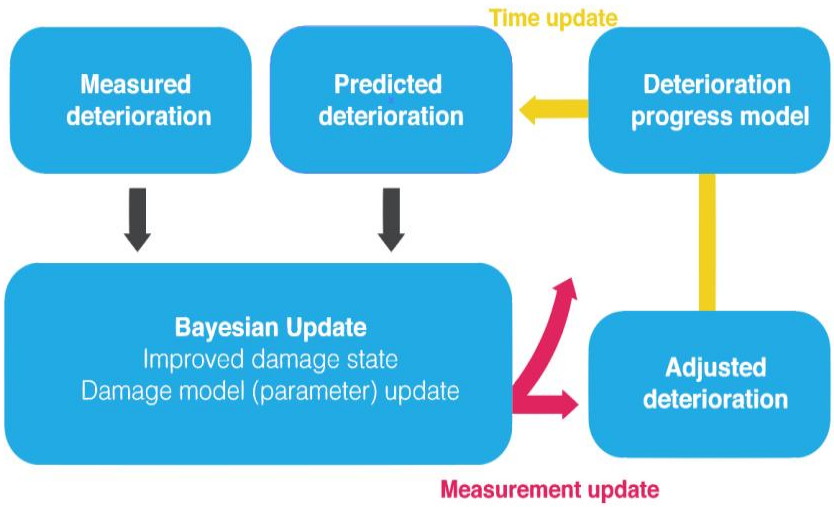

Figure 3 The bayesian filter algorithm for detecting obsolescence

However, practically some cases are happening such as the obsolescence model is not known in the process of predicting obsolescence, this study proves the efficiency of the prediction by recurrent neural network is proposed as a new method of predicting obsolescence, and its results are verified in the case of the methods that can solve the problem of compatibility of time series data mentioned above with the absence of a model machine learning is a field of artificial intelligence, which means that a technique that enables a machine to learn data directly, extract meanings and patterns, and classify and forecast information on its own. Deep learning which is one of the machine learning

methods is able to extract information and extract pattern information at a higher level than other machine learning methods by accumulating "deep" neural networks by combining various existing neural networks. Recurrent neural network, which is a representative algorithm of deep learning, is suitable for the problem that both input and output are composed of time series data and the sequences of materials and they are being applied to the modeling of important language and speech recognition, etc. Recurrent neural network applies the same task to all elements of sequential data, the output of the current element effects the output of the next element. The structure is shown in Figure 4. Theoretically, traditional recurrent neural networks are able to deal with long-term dependency problems (not learning long time patterns but only short-time relationships), but they are experiencing difficulties in reality. LSTM (Long Short Term Memory) has been developed in order to solve the long-term dependency problem of this recurrent neural network. LSTM, a variant of RNN, solves this problem. by introducing a cell state which consisting of input, forget and output gates in the "A" of Figure 4. In this study, LSTM is applied to the prediction of structure obsolescence

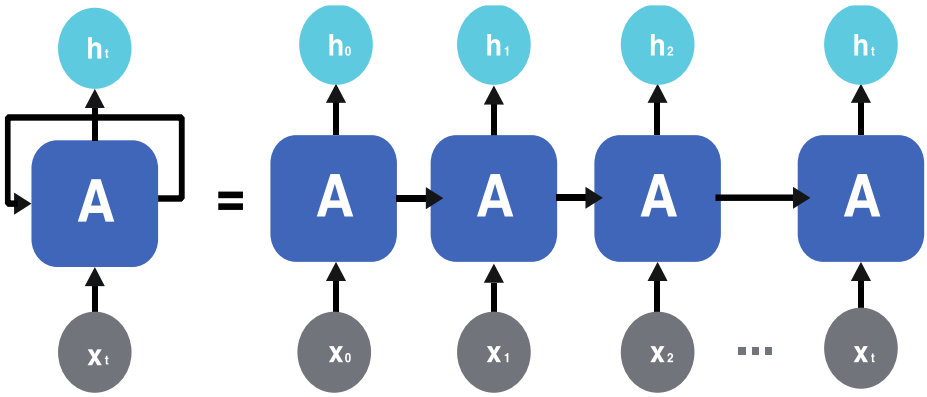

Figure 4 Graph represents visually recurrent neural network

Chapter 2. Recurrent Neural Network(RNN) and Long-short Term Memory (LSTM)

2.1. Recurrent Neural Network (RNN)

Recurrent neural network is one of a kind of deep learning. Deep learning is commonly used to perform classification and prediction of inputs. This deep learning proposes the predicts of the results by two important steps. First, construct the framework of the model by the learning step, and then perform the prediction with the model built through the prediction step. There are many kinds of neural networks in deep learning models with these characteristics. Neural networks are learning algorithms which perform the deep learning.

Of these various neural networks, the recurrent neural network, RNN, is the most suitable for predicting the obsolescence of a structure. The reason is that it is possible to predict through reflection of past data, unlike other neural networks, RNN accepts input values as dependent values and stores past information in memory.

2.2. Limits of Recurrent Neural Network (RNN)

However, there are two limitations in this RNN. The first is a long-term dependency problem. RNN stores past data in memory and uses it for prediction, but old data has a problem that it cannot be reflected in prediction. For example, refer to Figure 5, x_0 and x_1, which are far from the current value x_t on the time series data, are not properly applied to the prediction. This is not suitable for obsolescence prediction problems of structures that long time interval data should be observed and reflected.

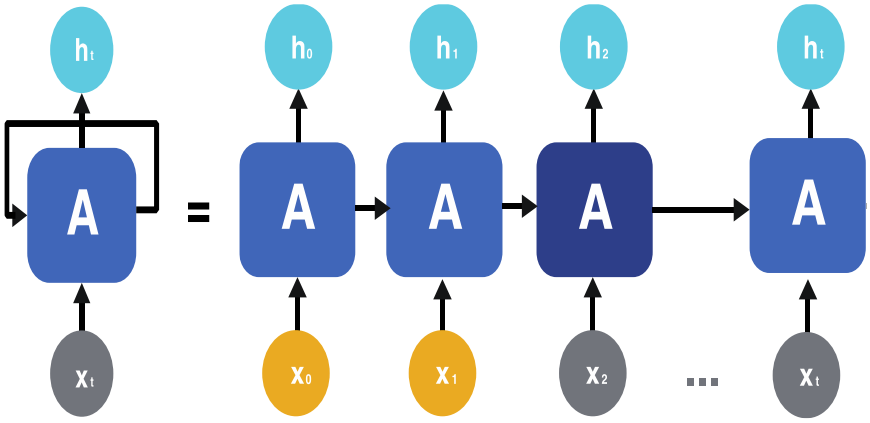

Figure 5 Visualization of long-term dependency problems of recurrent neural network

The second is a problem with gradient stabilization. If the result of the RNN converges to the local minimum, it will eventually be unable to reach the global minimum that supposed to be reached. Due to these two

problems, the RNN predicts incorrect values.

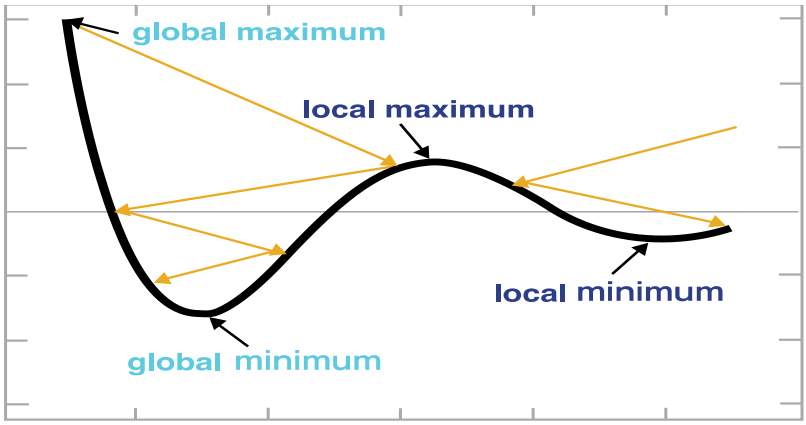

Figure 6 The process of reaching the local minimum and global minimum

2.3. Long Short-Term Memory (LSTM)

In 1997, a long short-term memory network, or LSTM network, was developed to solve these problems. LSTM network builds a new formulas model on each cell in RNN which is shown above, determine to decide how to control the dependence of long-term memory by parameter adjustment. In other words, it can optionally determine on long-term memory dependence, which enhances long-term memory dependence. Figure 7 shows the overall equation model of the LSTM model (This can be seen in Figure 7 by magnifying). First, in the green light, the arrow pointing to the right indicates the existing RNN model that is currently sending historical data to the current location. In addition to LSTM, historical data is the two

gates shown in the figure which combines information by determining weights of historical data and new incoming data. This increases the applicability of selective sorting of historical data and long-term memory. Through the LSTM model with these advantages, prediction and confirmation of obsolescence of the structure are possible.

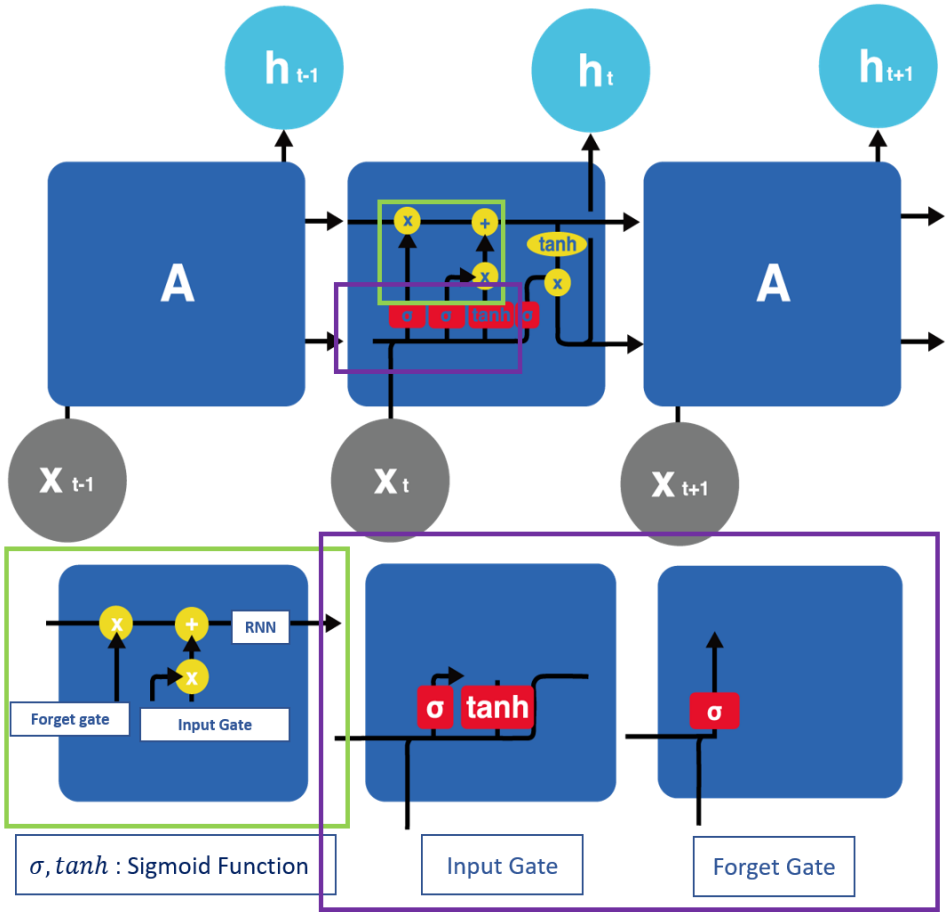

Figure 7 Diagram which represents detailed algorithm of LSTM

2.4. Window LSTM & Stacked LSTM

In the previous section, there was a specific LSTM algorithm for civil engineering structures. Among them, Window LSTM which is often used for time series data and Stacked LSTM are considered. Window LSTM and stacked LSTM are kinds of LSTM, which is a modification of the internal algorithm so that LSTM can be applied as to a given situation. The structure of the two algorithms is shown in Figure 8 and Figure 9. These methods can greatly enhance the contribution of past data by internal algorithms, which is expected to be more suitable for the obsolescence problem of structures with long time interval data than existing LSTM. Obsolescence of the structure is predicted as each algorithm is modified and applied to the current problem along with the existing LSTM.

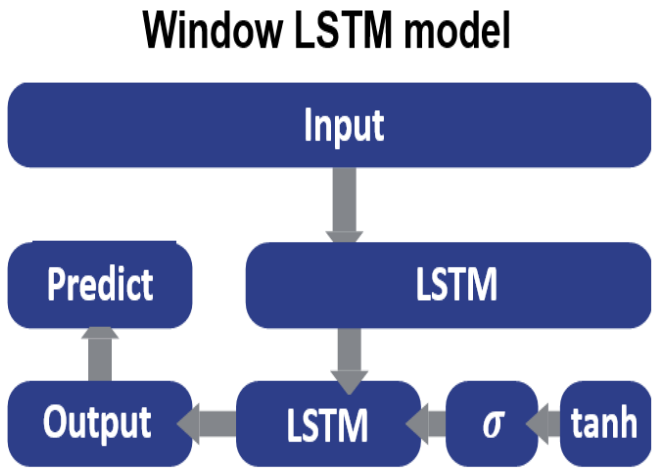

Figure 8 Diagram showing algorithm of window LSTM

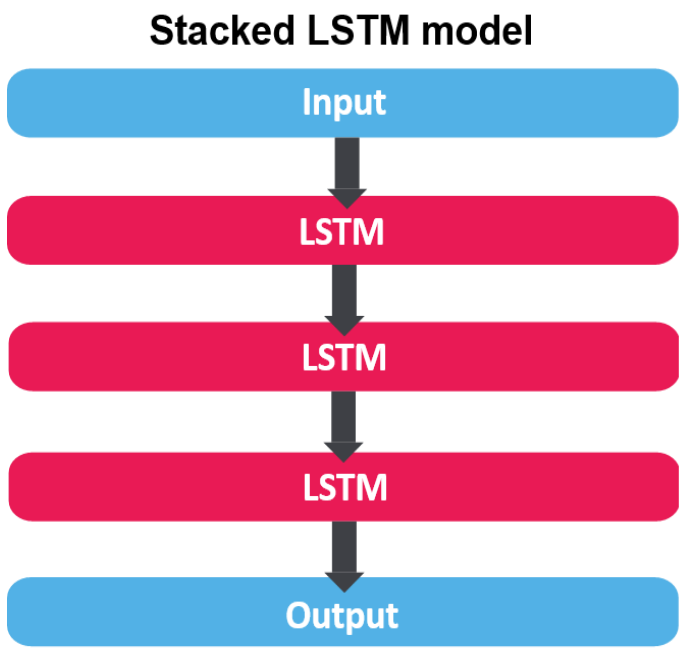

Figure 9 Diagram showing the algorithm of stacked LSTM

Chapter 3. LSTM approach of Corrosion Progress Model

3.1. Corrosion Progress Model (Engelhardt and McDonald, 2004)

The following models are the Corrosion Progress Model (Engelhardt and McDonald, 2004) used to predict obsolescence. This model draws the changes over the time at the point where the corrosion of the structure begins, using the parameter values and the corrosion rate $V(t)$, consciousness shown in (3.1), (3.2). Here the parameters are 5 kinds, V_0, α, t_0, τ, σ_0 . Also used the normal distribution wiener process $W(t)$, which is proportional to the dispersion time as an uncertainty value.

$$V(t) = \frac{dD}{dt} = exp\left(ln(V_0) + (\alpha - 1)ln\left(1 - \frac{t-t_0}{\tau}\right) + W(t) - \frac{t-t_0}{t_f - t_0}W(t_f)\right) \quad (3.1)$$

$$\Lambda(t) = ln(V_0) + (\alpha - 1)ln\left(1 + \frac{t-t_0}{\tau}\right), t \geq t_0 \quad (3.2)$$

V_0 : initial corrosion rate
t_0 : starting time
α , τ and σ_0 are positive constants.
$(0 < \alpha < 1, 0 < \tau, 0 < \sigma_0)$
D : corrosion depth
t_f : repassivation time

Each parameter V_0 is the initial corrosion rate, t_0 is the time at which corrosion begins, and (α, t_0, σ_0) is a positive real value determined by the initial state of the structure. σ_0 and τ are values that do not change with the situation. Data sets were randomly selected for 20 as shown in Figure 10 and the initial values are set to t_0 for 5, V_0 for 0.6, α for 0.15, τ for 4, and σ_0 for 0.1.

However, there are some assumptions to express the corrosion of the structure in this way. First, the corrosion rate must converge to a certain value after a sufficient time has elapsed. Second, the corrosion of the structure is impossible to recover. In the study, 20 scenarios were obtained through the model. The corrosion depth, which is actually observable, is plotted by integration as Figure 11.

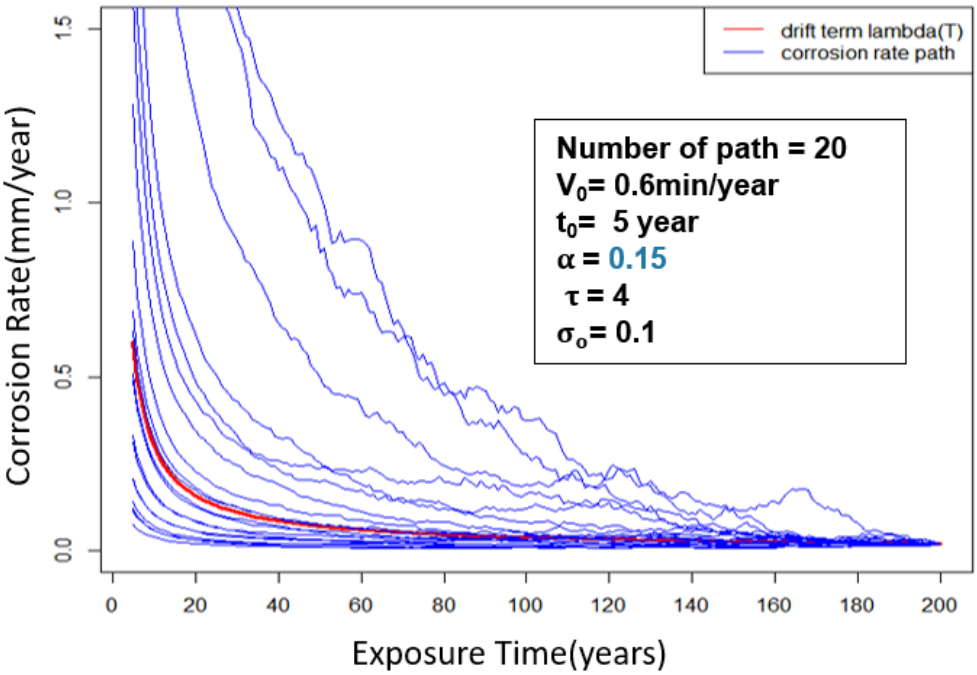

Figure 10 20 virtual data graphs randomly extracted from corrosion progress model

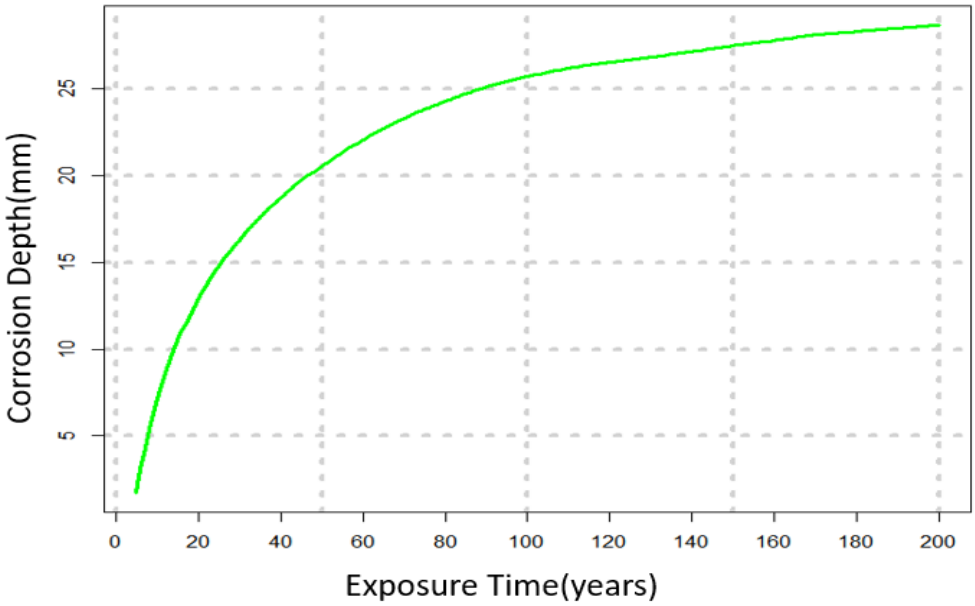

Figure 11 Corrosion rate graph integrated and represented as corrosion depth over time

However, τ and σ_0 have almost no change depending on the type of structure, but in case of α, it is a value that needs to clearly specify the range of the value. Thus, the graph is plotted about α which is bigger than 0.5 (Figure 12 : α =0.8), this brought the result of violating the existing assumption that sufficient time should be allowed to converge on a certain value. In conclusion, α was used in this study as '0.15', one of the non-hypothetical values.

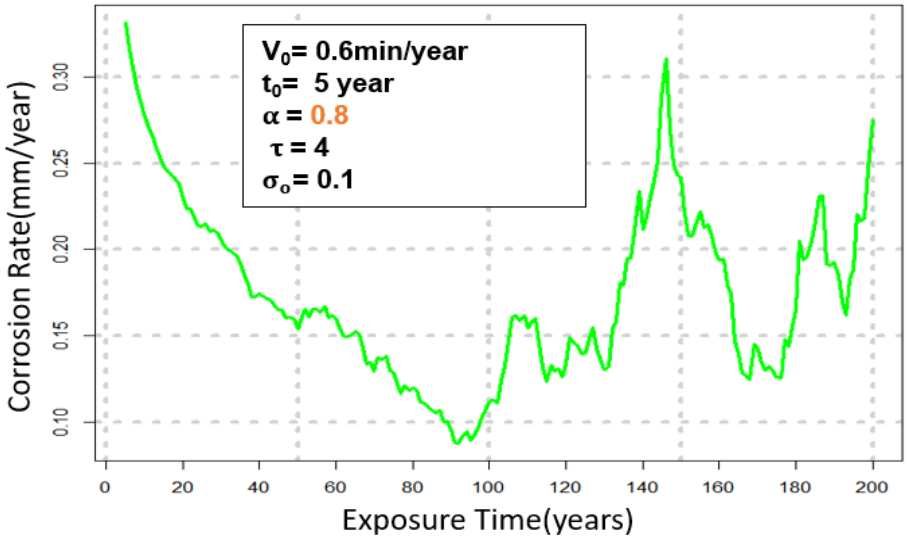

Figure12 Graph of corrosion rate over time with α = 0.8

3.2. LSTM approach - Effect of Number of Base Training Data Sets

This is the process of applying the LSTM model about the 20 scenarios obtained. In this case, for ease explanation, plotted the corrosion rate instead of the corrosion depth. Refer to the Figure13, blue is the measured data, monitoring data. Before applying the LSTM to the blue graph, the LSTM model is pre-trained for up to 200 years about the base training data set, or similar obsolescence phenomenon. When the learned LSTM model is applied to the monitoring data, the data up to that period are re-learned in the model and finally predicted with assumption that the data up to 140 years old was given. The result of re-learning the previously trained model with new data is the green graph and the graph that predicts values after 140 years is the red color, LSTM prediction.

If training is given on two different hypothetical scenarios shown in Figure 14, which is similar obsolescence phenomenon during training before learning, the results will be different. The performance of LSTM is verified by the ability to predict improved results with current data and there is a difference between the red and blue graphs, it is visually confirmed that the second trainee shows less error. For a more accurate comparison, plotted the first and third quartile values and the mean value

when the LSTM is performed 30 times so that the error value at 200 years is represented by the Root Mean Square Error(RMSE) shown in Figure 15 and Figure 16. Root Mean Square Error(RMSE) is a quadratic scoring rule that also measures the average magnitude of the error. As in (3.2), it's the square root of the average of squared differences between prediction and actual observation.

$$RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - \hat{y}_j)^2} \tag{3.2}$$

When training with two sets of data, comparing the RMSE mean values shows that the error has become smaller.

To verify the performance of the LSTM as described above, it is important to check the error or RMSE value at a specific point in time according to the change in the number of base training data sets and also performance verification based on in-operation training time is required. (There is the value set for 140 years.) These two variables verify the performance of LSTM.

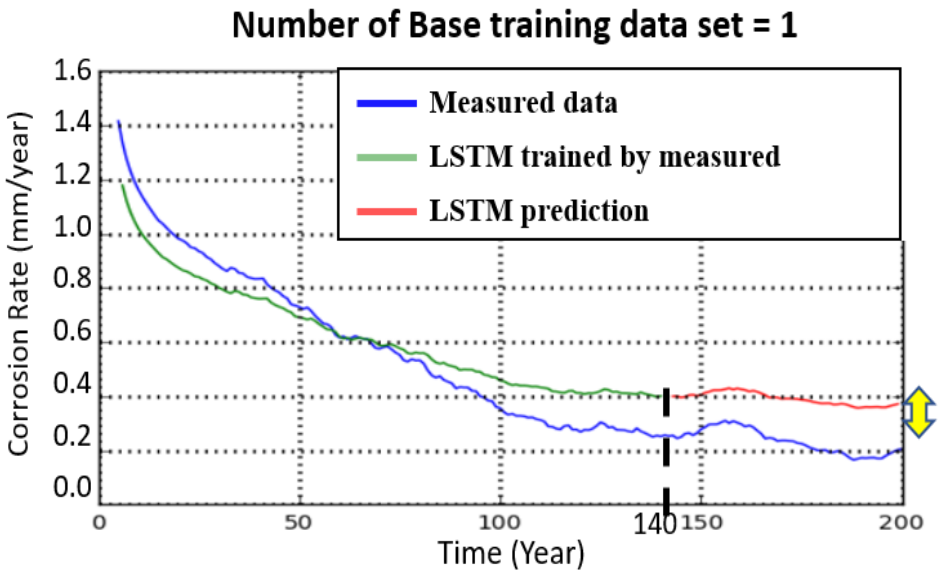

Figure 13 The measured value and LSTM predicted value graph when the number of base training data sets is 1

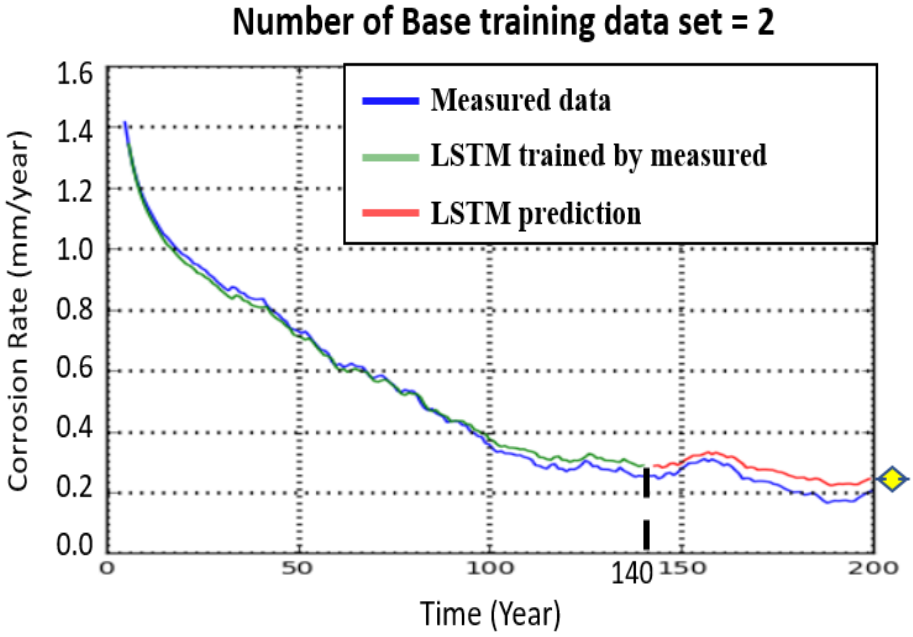

Figure 14 The measured value and LSTM predicted value graph when the number of base training data sets is 2

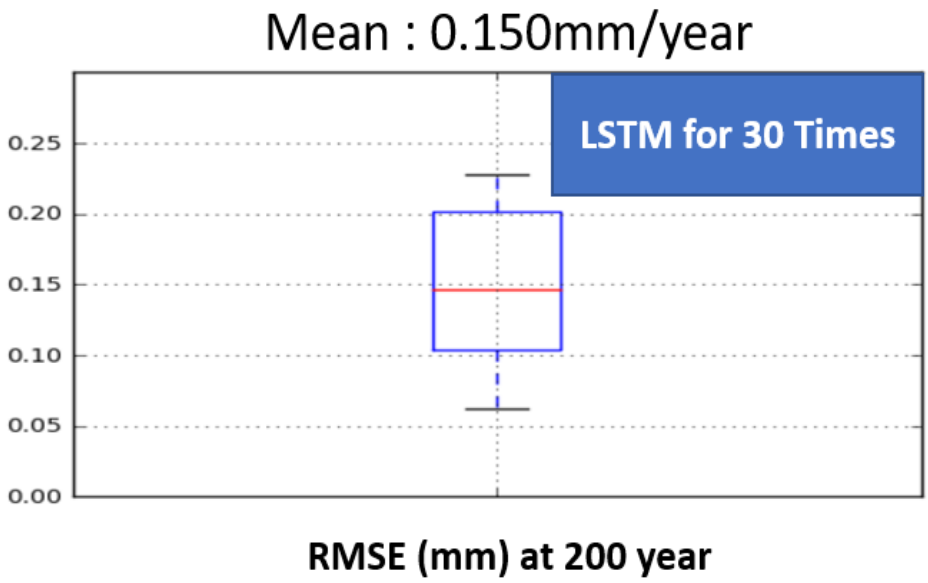

Figure 15 Graph represents the error value as box plot at 200years point in Figure 13

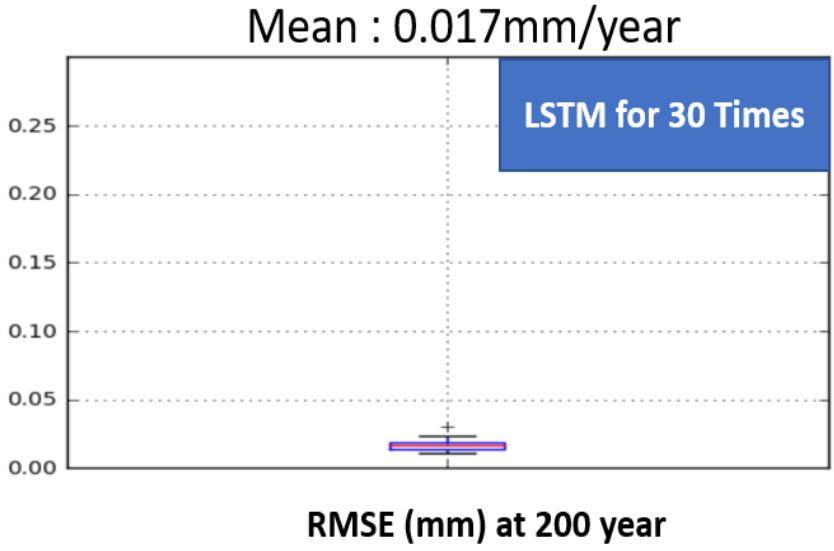

Figure 16 Graph represents the error value as box plot at 200years point in Figure 14

Chapter 4. Application of LSTM to Prediction of Corrosion Progress

4.1. Prediction of LSTM model

The Figure 17 shows the results of natural, window, and stacked LSTM in order from left to right. The error from the current 50 years is calculated, and the color and contour lines represent the respective RMSE values. The darker color shows the smaller the error. As it is shown visually from the heat map, it is confirmed that the larger the size of in-operation training time and base training data set, the error is getting smaller. This is consistent with the results previously predicted and demonstrates the performance of LSTM. Likewise, window and stacked LSTM have the same result. In order to visually compare the performance of the natural LSTM with the performance of the other two, it has shown as a boxplot just as Figure 18. The difference in color indicates the change in the base data training set, and the box plotted the error according to the in-operation training time as the first and third deciles and the mean value. As it is shown in a boxplot, window, stacked, and natural LSTM have less error on average.

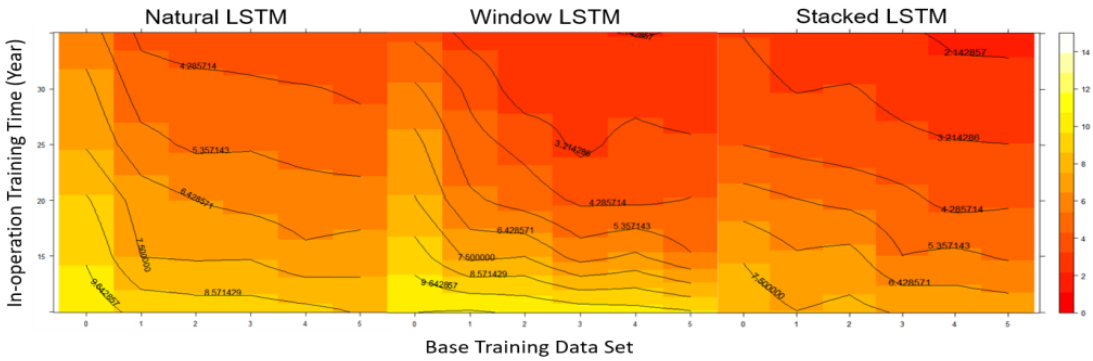

Figure17 Heat map of results of 50 years of natural, window, stacked LSTM of corrosion progress model

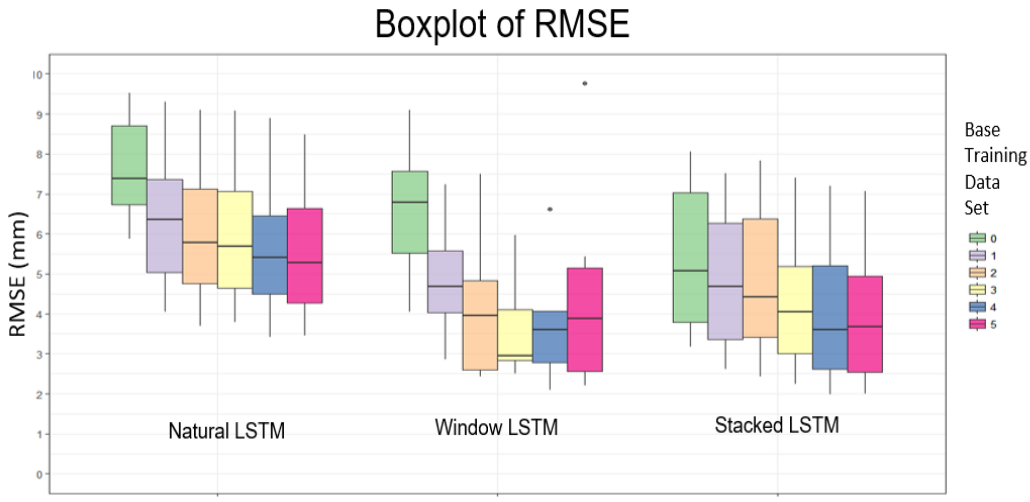

Figure18 The results of Figure 17 are selected by the number of base training data sets and expressed in boxplots

4.2. Comparison of Natural, Window, Stacked LSTM model

For specific comparison, shown in Figure19, the results are plotted that when the base training data set was fixed for each value and when the in-operation training time was fixed at 5-year intervals. Red lines indicate natural LSTM, green indicates window, blue indicates stacked LSTM. When the base training data set is fixed, green and blue are both lower than red. Likewise, when the in-operation training time is fixed, the same tendency is observed. This suggests that window and stacked LSTM are better than natural LSTM in terms of obsolescence. More results from Figure 19 are able to be found in Appendix A.

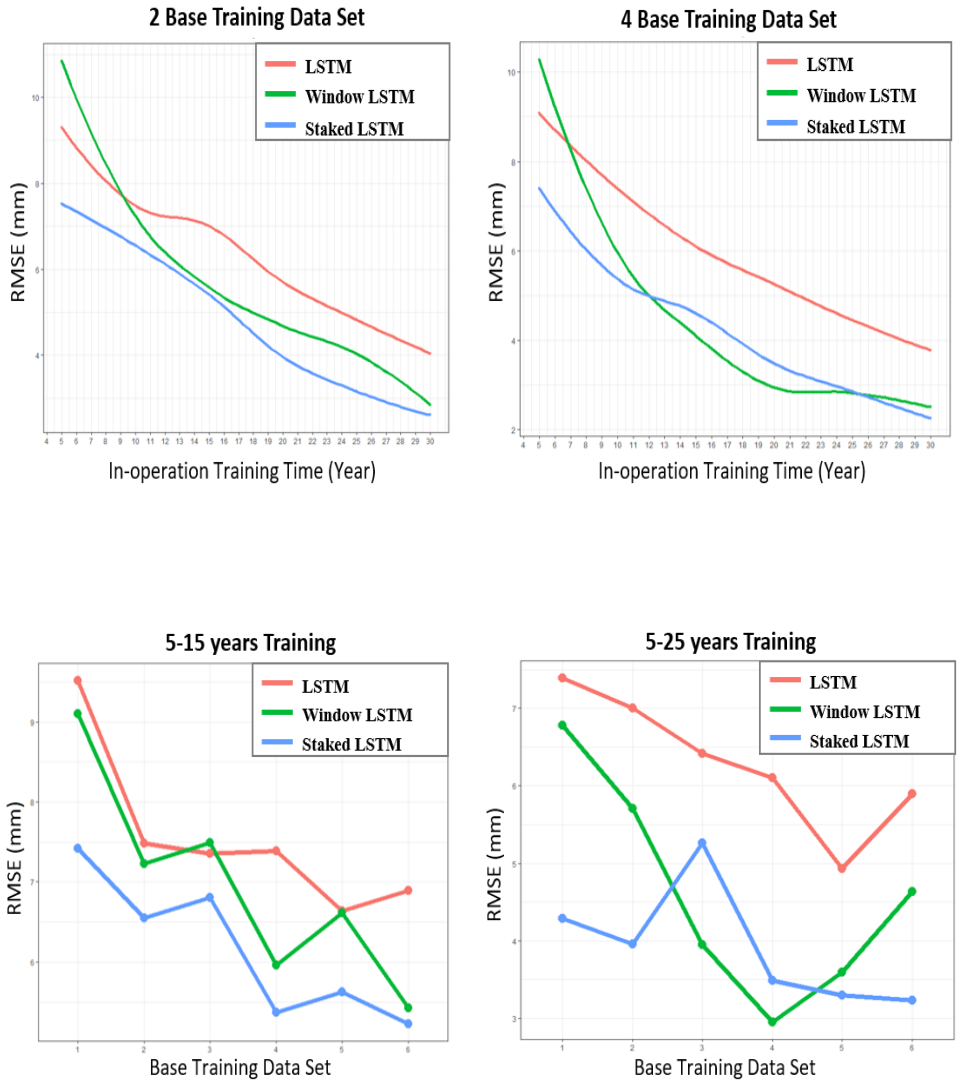

Figure 19 Graph of LSTM results with fixed number of base training data sets, graph when in−operation training time is fixed

4.3. Comparison with Particle Filter

By comparing the result value with the particle filter, comparison of the results with the particle filter are described. The particle filter has 5 monitoring data inputs up to 22 years, and the results at 50 years have an average of 7.73 mm error for 20 scenarios. Figure 20 shows how the particle filter works and the red shaded area shows the error range when it has five monitoring data inputs.

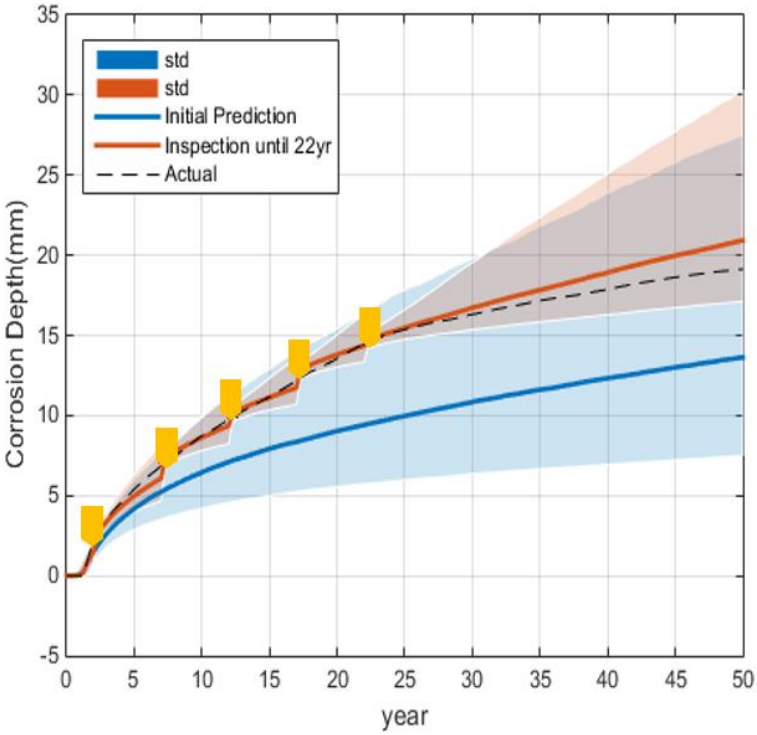

Figure 20 The process of applying 20 data sets of the corrosion progress model on the particle filter

For comparison under the same conditions as the LSTM model, in three LSTM heat maps, the results of learning the model up to 27 years and the results of setting the base training data set to five were collated and compared with the particle filter.

As a result, as shown in Figure 22, LSTM showed better results regardless of the number of base training data sets when 27 years of training, and LSTM showed better results when more than 8 years of observation data were set with 5 base training data sets. This result is applied for all three natural, window, stacked LSTMs. This confirms that the LSTM model produces better results than the particle filter in the obsolescence problem of the structure.

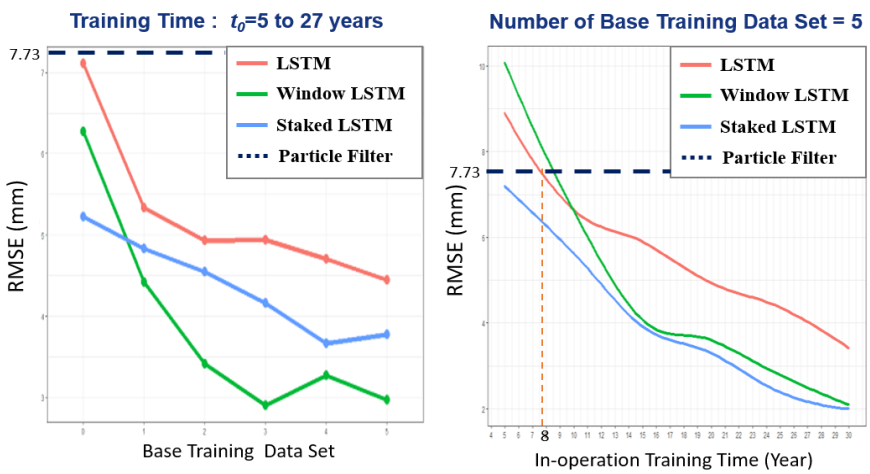

Figure 21 Comparison of natural, window, and stacked LSTM results with particle filter results

Chapter 5. Conclusion

This study proposed a new methodology to combine obsolescence model and monitoring data by recurrent neural network.

Additionally, this study proposes that a new LSTM algorithms (Window LSTM, Stacked LSTM) according to the characteristics of each subjects, enabling high-accuracy prediction that is appropriate for the situation. This suggests that new algorithms for the situation is able to be created continuously. In addition to this, the concept of the base training data set and the in-operation training time are presented to enable the installer to set the accuracy by the user, and can perform operations based on this.

Studies are being conducted to verify the efficiency and applicability of the developed methodology through numerical examples and also recurrent neural network structure is also under development. For making most efficient way to increase the accuracy of obsolescence prediction current methodology has used the strain and displacement available from the finite element model as the structural monitoring data. However subsequent study is required to apply the response of the structure such as the acceleration obtained from the health monitoring data of actual structures in the future.

Appendix A

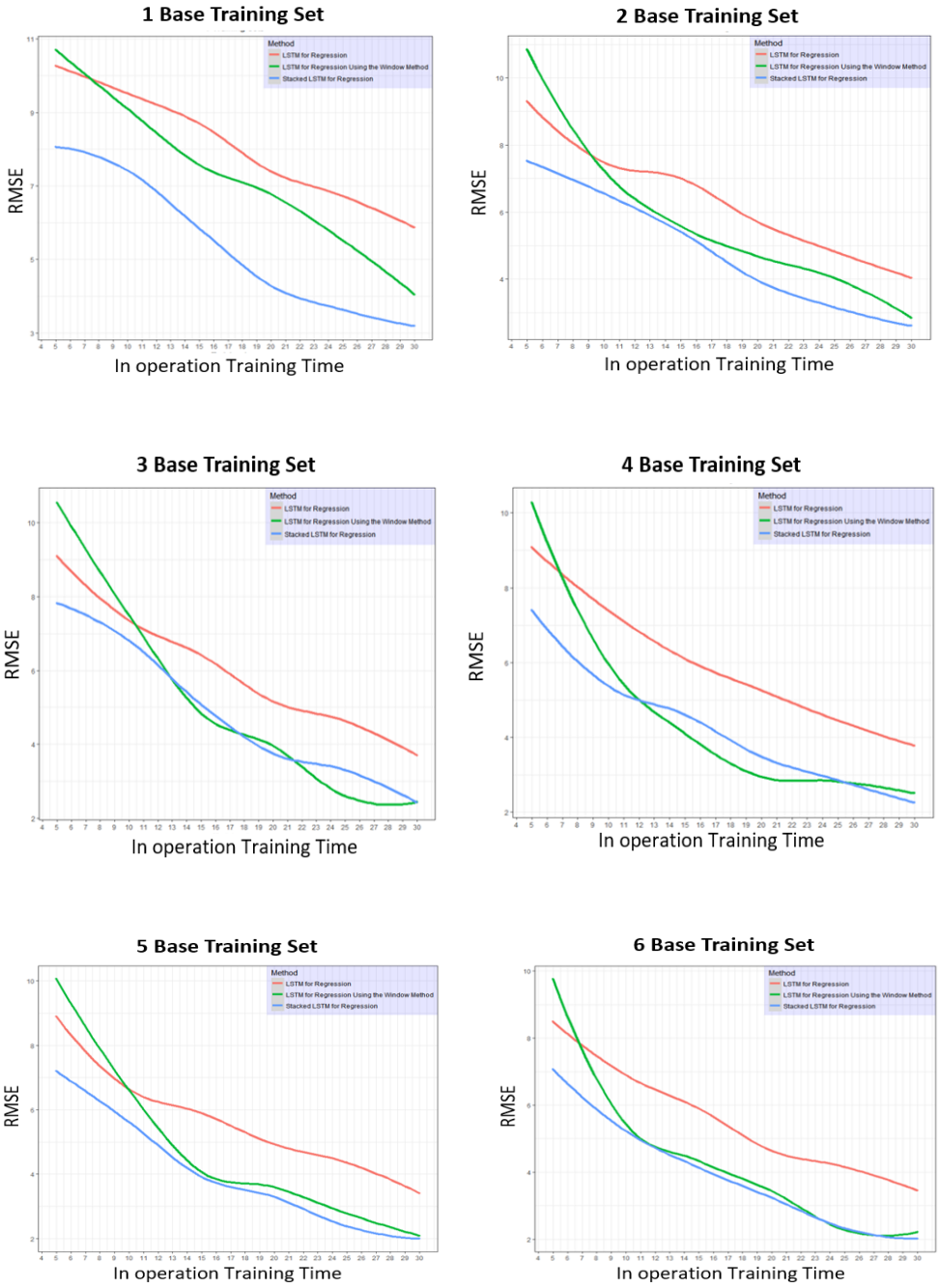

Figure A 1 Graph of LSTM results with fixed base training data sets

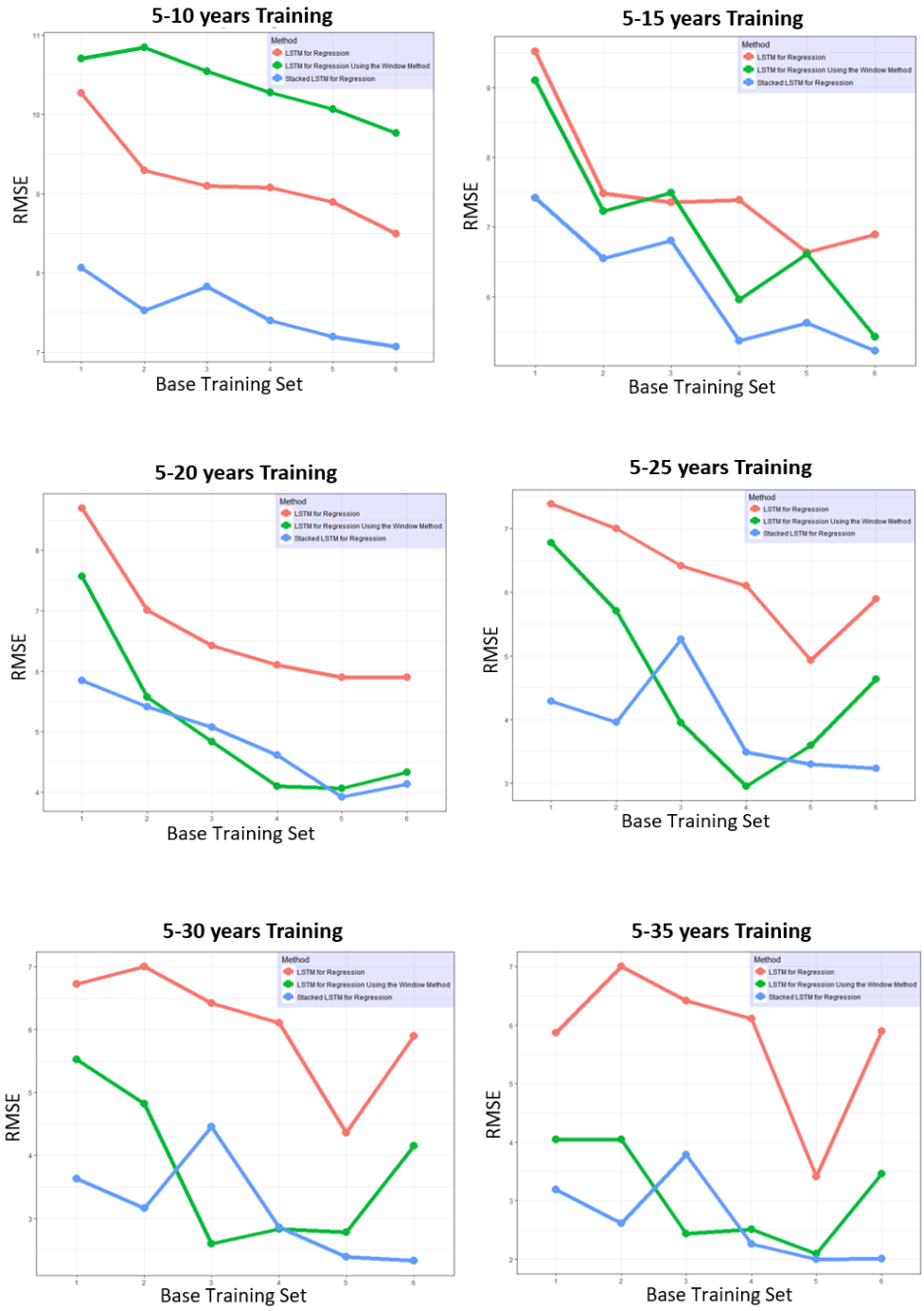

Figure A 2 Graph of LSTM results with fixed In-operation training time

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국 문 초 록

구조물의 열화 및 노후화는 다양한 불확실성 요인으로 인하여 선제적 예측이나 그에 따른 대응에 한계를 보인다. 이를 극복하기 위해 본 연구에서는 딥러닝 알고리즘의 하나인 순환신경망 (Recurrent Neural Network, RNN)을 활용하여 운용 중 얻어지는 구조물의 건전성 모니터링 (Structural Health Monitoring, SHM) 데이터와 역학 지식에 기반한 열화 진행 모델을 결합하는 방법론을 제시하고자 한다. 순환신경망은 시간 순서로 받아들인 입력데이터를 학습할 때 사용하는 딥러닝 방법론으로서 현재는 언어 인식 및 모델링 분야에 활발히 적용되고 있다. 순환신경망을 통하여 모니터링 데이터를 통해 재귀적으로 업데이트함으로써 구조물의 노후화에 대한 정확한 예측과 평가가 가능할 수 있다. 이는 기존 노후화 예측모델의 결과와 비교함을 통해서 그 성능을 확인할 수 있고, 또한 base training data set의 수에 따른 결과를 확인함으로써 순환신경망 모델의 정확도를 결정한다. 또한, 기존 순환신경망을 적용하는 것뿐 아니라, 구조물의 노후화에 적용할 수 있는 새로운 알고리즘을 제시함으로써 그 성능을 검증하고 더 나은 예측을 가능케 한다.

주요어 : 순환신경망, 머신러닝, 구조물 열화 및 노후화, 의사결정

학 번 : 2016-21276