Seoul National University
Department of Civil&Environmental Engineering

SSRG
Structural & System Reliability Group

Application of Recurrent Neural Network to Prediction of Structure Deterioration

구조물 노후화 예측을 위한 순환신경망 방법론의 적용

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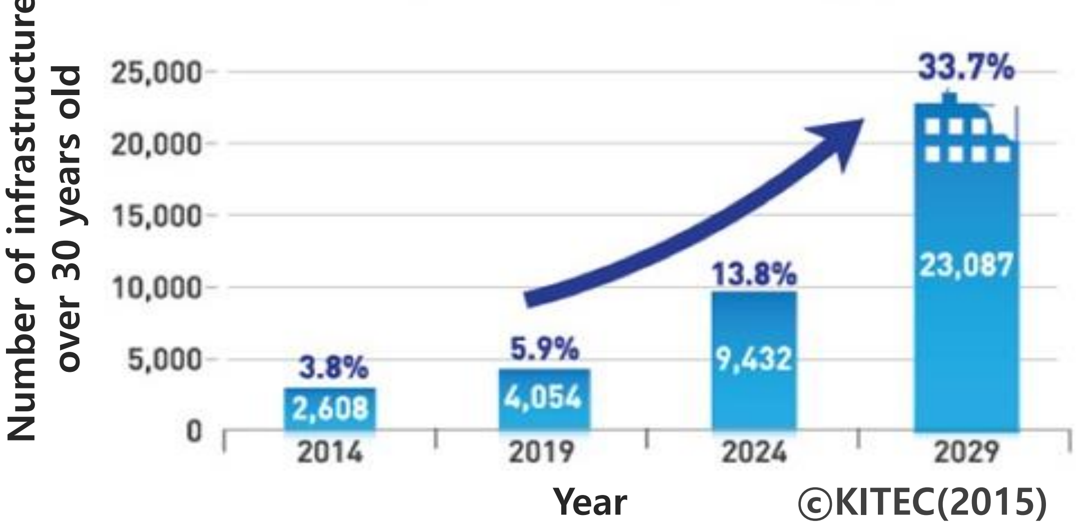
Contents

Introduction
Motivation

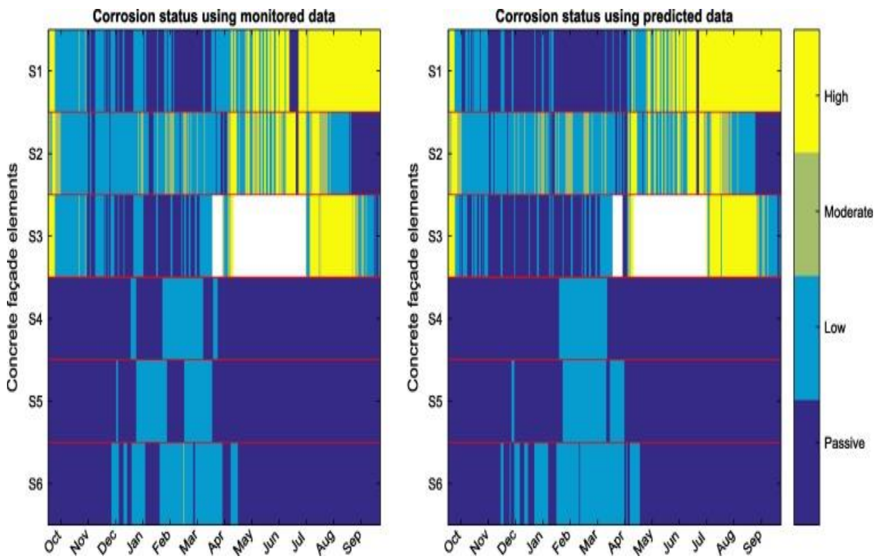
- The proportion of **aging infrastructures** is expected to increase up to 33.7% by 2029.
- For the effective structure management within a limited budget, structure maintenance planning should be optimized using **structure deterioration prediction.**
- However, structure deterioration prediction using **deterioration progress model** is often **inaccurate**.

Aging infrastructures trends (Korea)

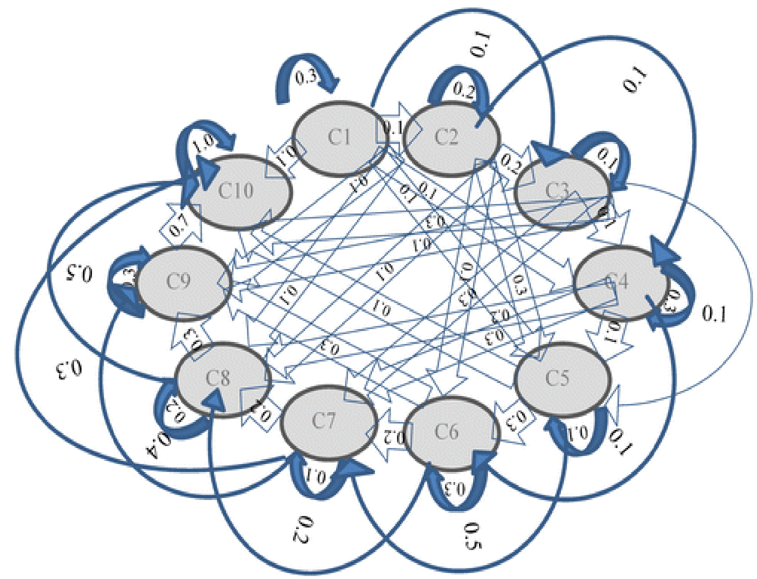


Existing Methodologies

Hygrothermal Prediction (Zewdu & Sistonen, 2011)

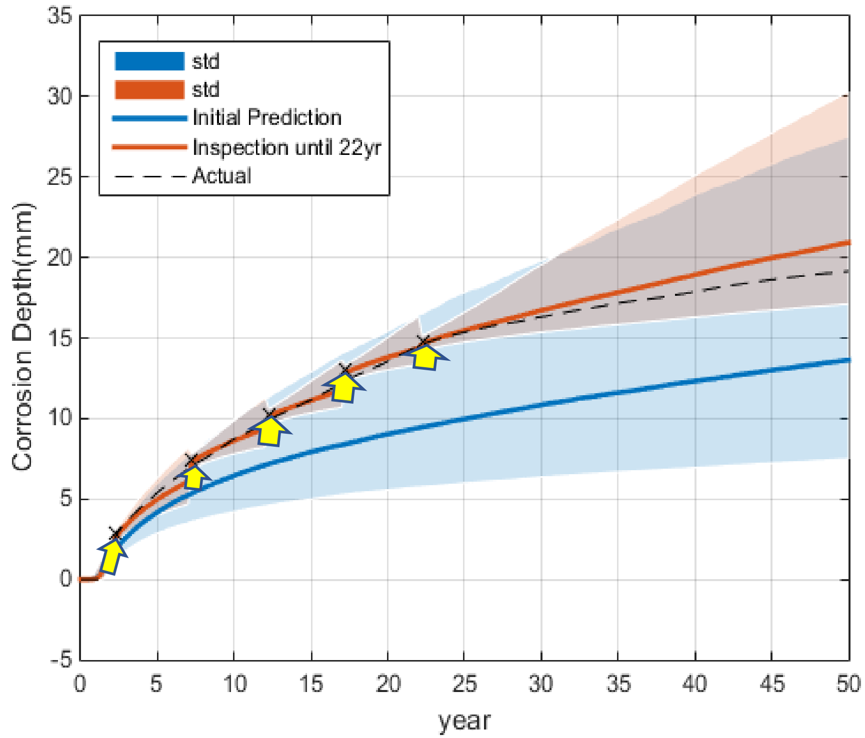


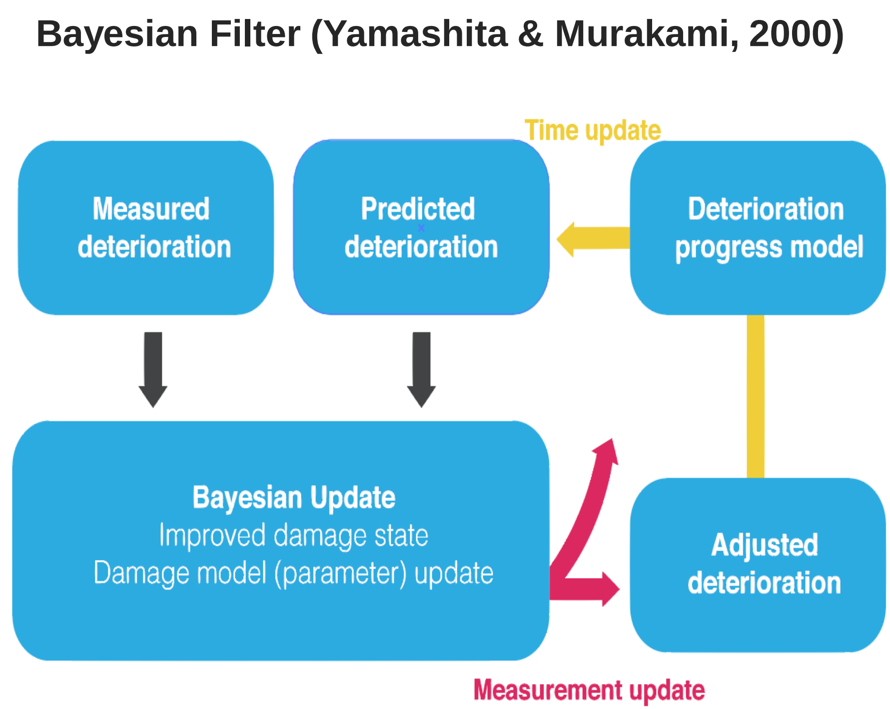
Markov Deterioration Model (Setunge & Zhang, 2014)



- Hygrothermal prediction and markov deterioration model is one of the mostly used deterioration progress model.
- As the number of the input data size increases, accuracy and the effectiveness of both hygrothermal prediction and Markov deterioration model decrease.
- Time-series data is not applicable for these two models.

Existing Methodologies : Particle Filter



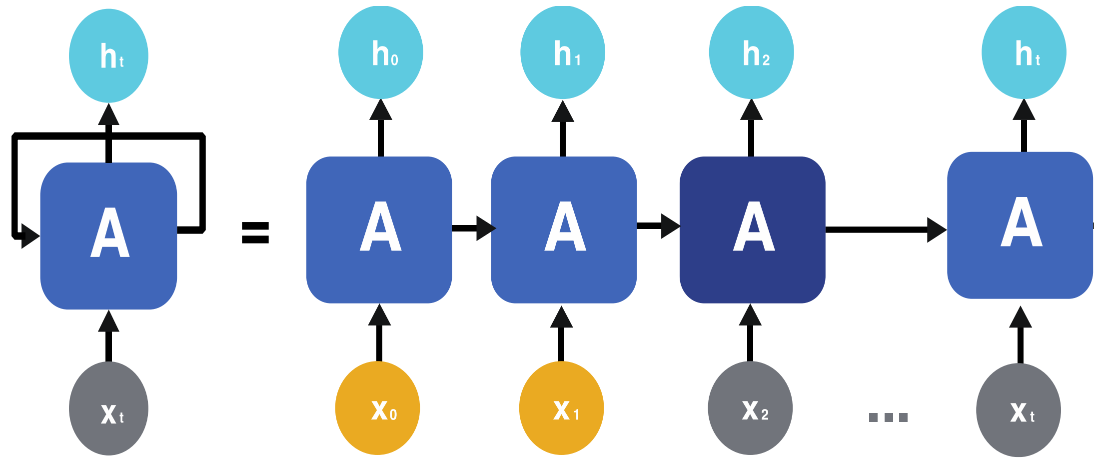


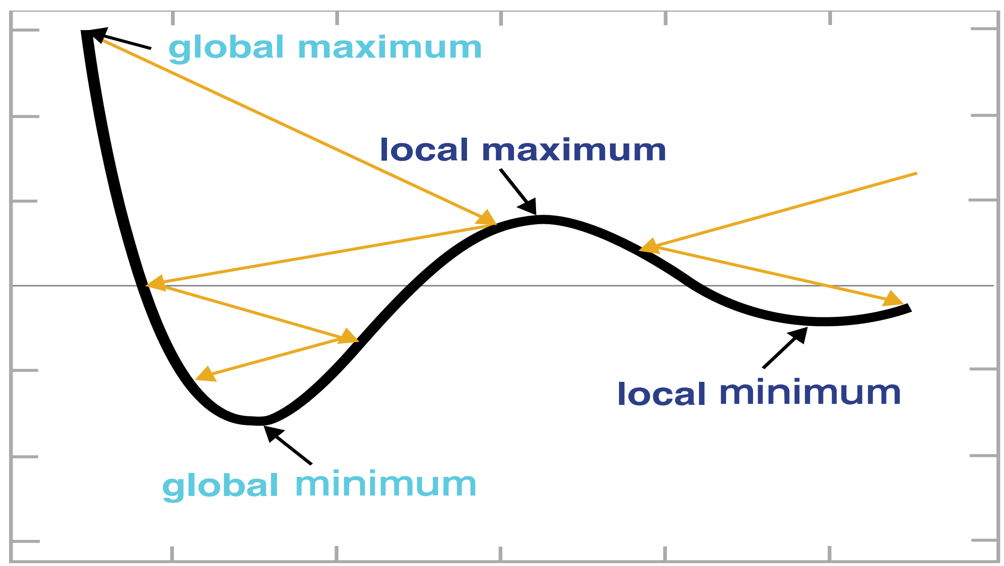
- Full simulation based filtering method & probability based data-model assimilation.
- Indirect measurement can be incorporated.
- Monitoring/Inspection data should be used to predict future deterioration pattern.
- Each results give new parameters of the model.

Deep Learning for Prediction of Deterioration

Recurrent Neural Networks (RNN)

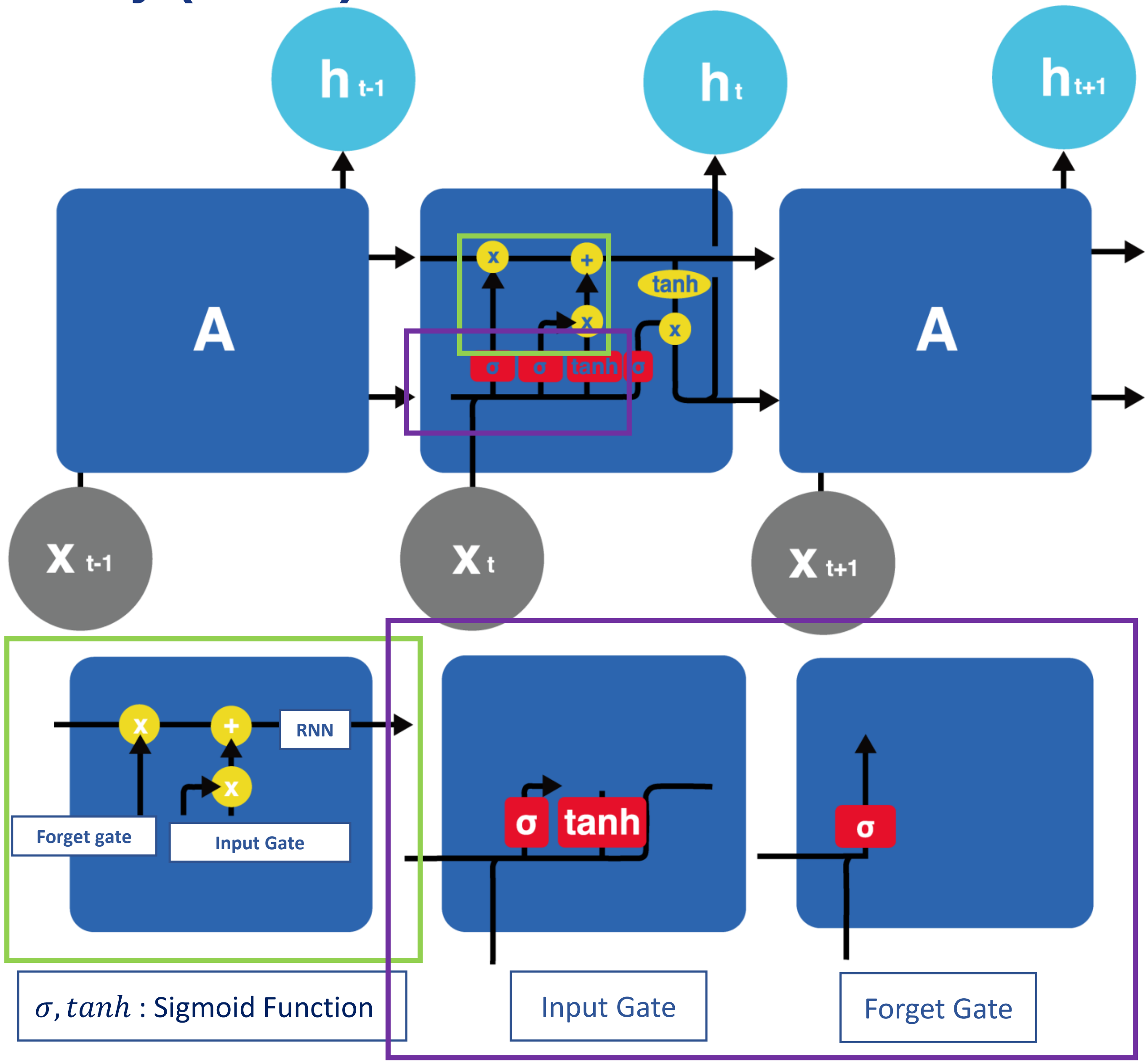
- Deep learning algorithm(Neural Network model) has 2 phases : Training phase & Prediction phase.
- In a traditional Neural Network, it assumes that all inputs (and outputs) are independent of each other.
- RNNs can use their internal memory to process arbitrary sequences of inputs.
- It is appropriate for the time sequential data problem like predicting the structural deterioration.





Long Short-Term Memory (LSTM)

- Special kind of RNN, capable of learning long-term dependencies. (Hochreiter & Schmidhuber ,1997)
- Remembering information for long periods of time is practically its default behavior.
- In this study, LSTM is used to predict the deterioration of structures. The LSTM is developed using Keras with Python.



Research Goals and Methodologies

Limitation of existing approach

- Existing prediction model may not be appropriate for evaluating structural deterioration.
- It shows their limitation on long-term problem which inputs are sequential data.

Methodologies and Goals

❖ **Development of LSTM-based Framework for Corrosion Prediction**

- Develop Long Short-Term Memory model which is trained with several monitoring data. Show the developed model can predict the deterioration output accurately.

❖ **Application to Numerical Examples**

- Application of the LSTM model to corrosion progress model. Identify the difference between the monitoring data and prediction of LSTM.
- Show the performance of LSTM model using the number of base training data set and in-operation training time.

❖ **Comparison with other approches**

- Compare the results of the LSTM model on corrosion progress model with those by other approach such as Bayesian Filter.

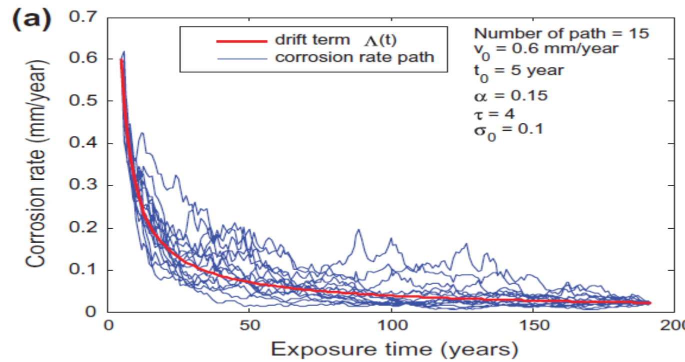
Corrosion Progress Model
(Engelhardt and Macdonald, 2004)

Corrosion rate is known to have the form of

$$V(t) = \frac{dD}{dt} = \exp\left(\ln(V_o) + (\alpha - 1)\ln\left(1 - \frac{t - t_o}{\tau}\right) + W(t) - \frac{t - t_o}{t_f - t_o} W(t_f) \right)$$

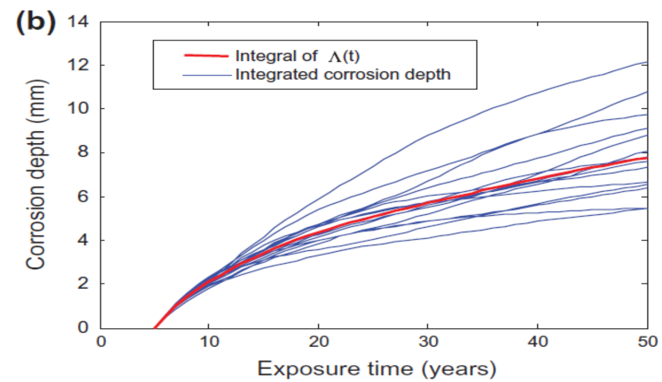
$$\Lambda(t) = \ln(V_0) + (\alpha - 1)\ln\left(1 + \frac{t - t_0}{\tau}\right), t \geq t_0$$

V_o : initial corrosion rate
t_o : starting time
α , τ and σ_o are positive constants.
($0< \alpha <1$, $0< \tau$, $0<\sigma_o$)
D : corrosion depth
t_f : repassivation time



❖ Uncertainty considered in corrosion progress

- $W(t) \sim N(0, \sigma_o^2 t)$: *Wiener process*
- Corrosion progress model parameters $V_o, \alpha, t_o, \tau, \sigma_o$
- Measurement error



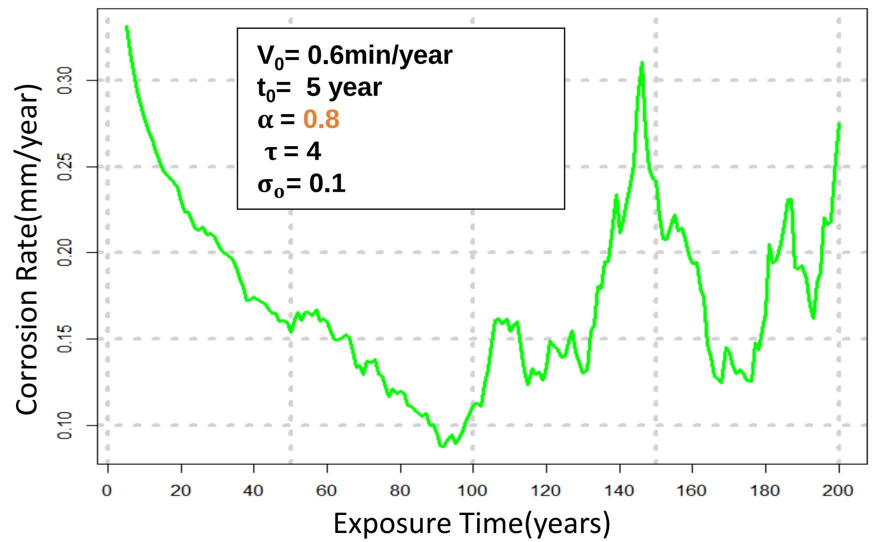
❖ Corrosion propagation at a given site is based on the following considerations

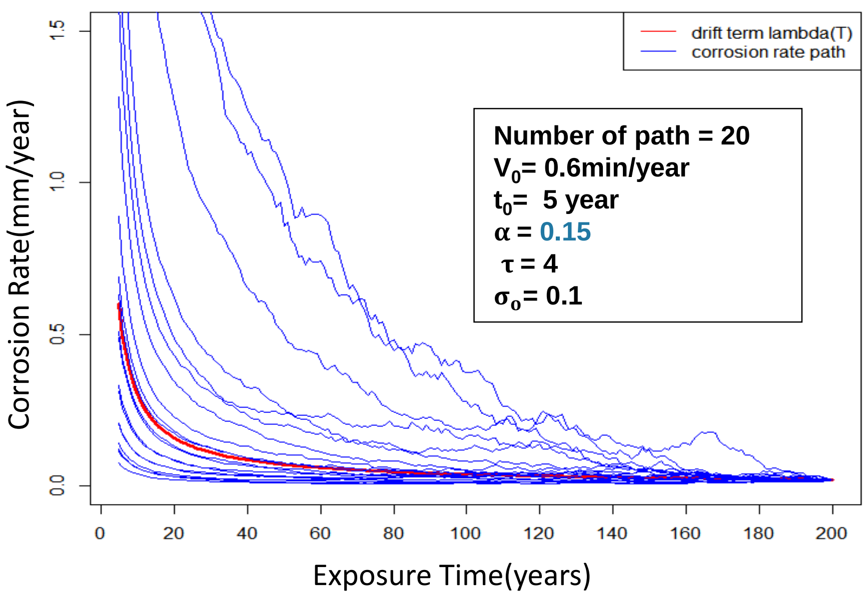
- The corrosion damage is irreversible.
- The growth of external corrosion depth is monotonic.
- The corrosion rate will finally reach a stationary value after a long period of exposure.

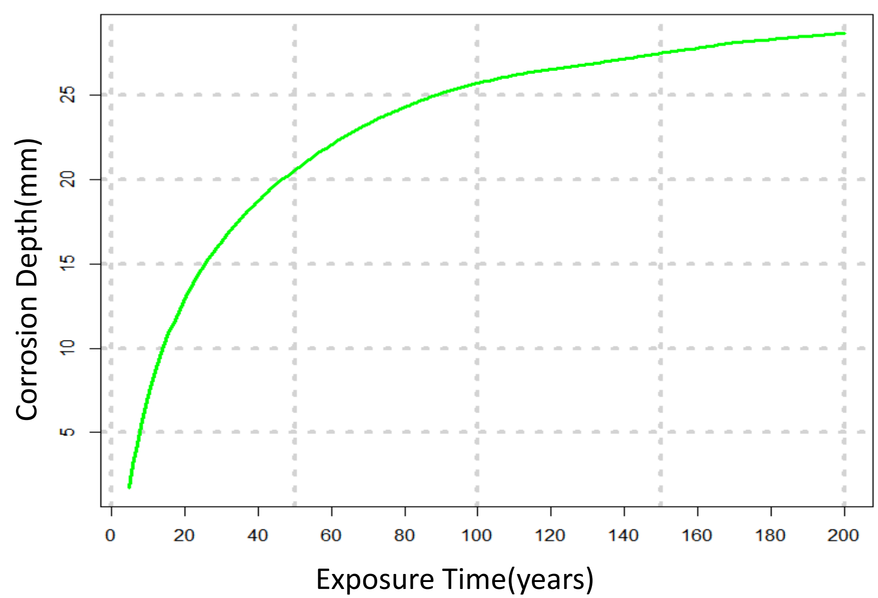
Corrosion Progress Model

Data set

- Except t_0, other parameters can be considered as common arguments in the model for a given cluster.
- In this research, corrosion depth is used at 50 year to verify the error (Root Mean Square Error).





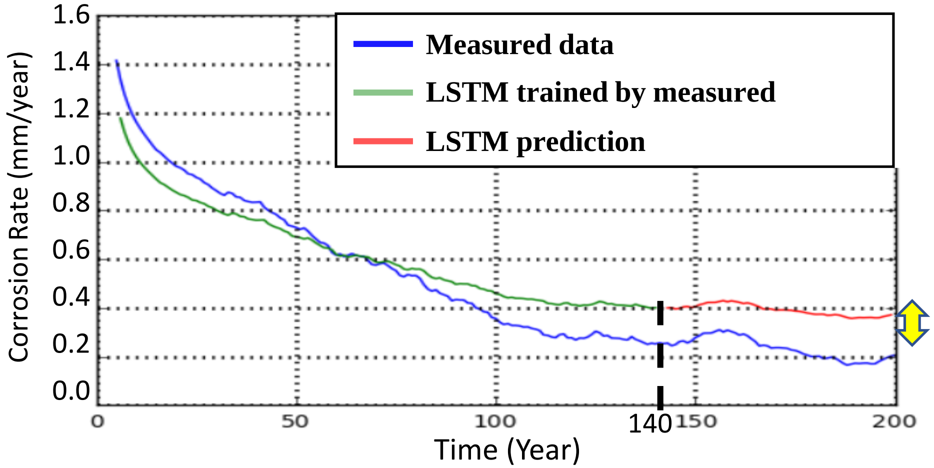


Corrosion Progress Model – LSTM approach

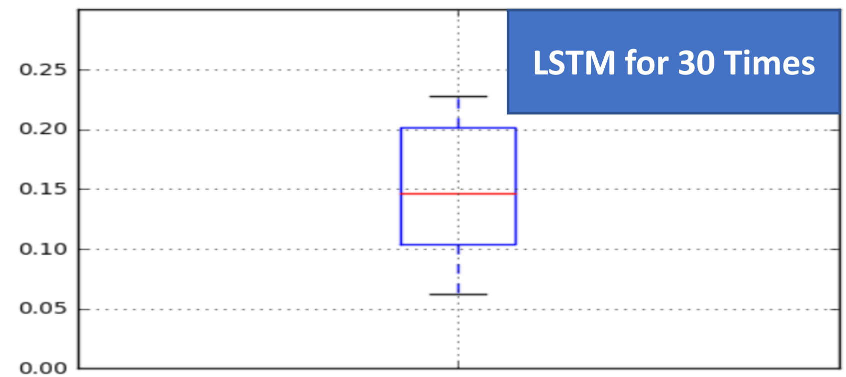
Effect of Number of Base Training Data Sets.

- The results show that, as the number of base training data set increases, RMSE (Root Mean Square Error) is decreased.

Number of Base training data set = 1

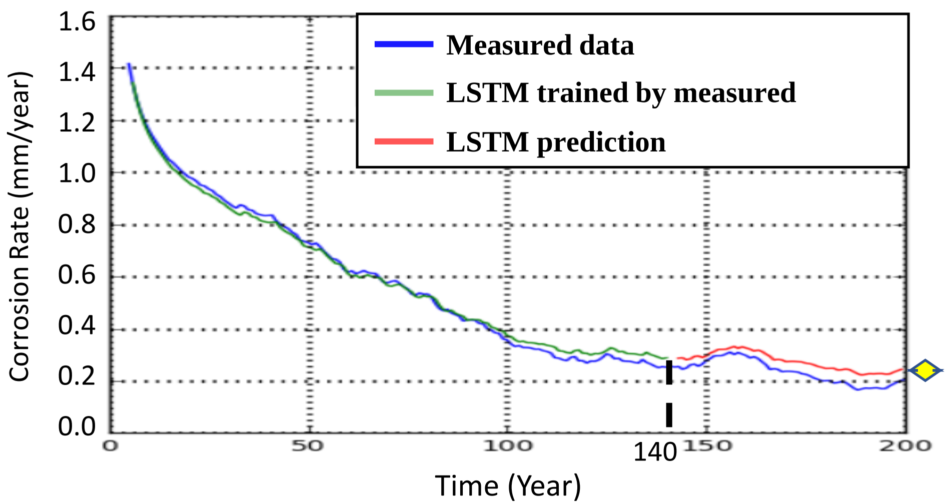


Mean : 0.150mm/year

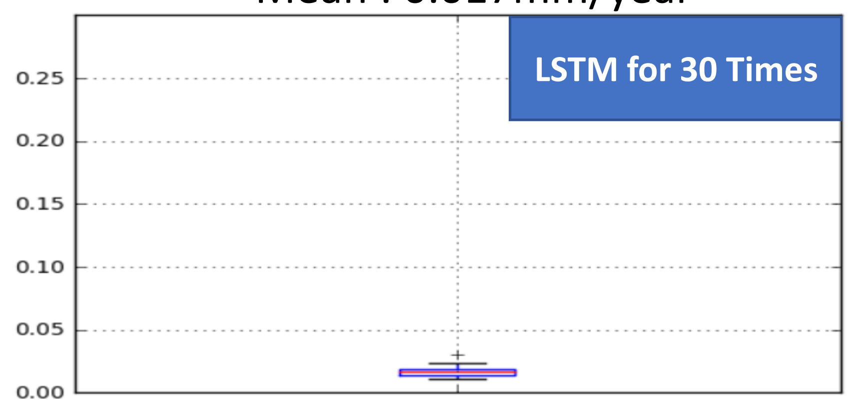


RMSE (mm) at 200 year

Number of Base training data set = 2



Mean : 0.017mm/year



RMSE (mm) at 200 year

Window LSTM & Stacked LSTM

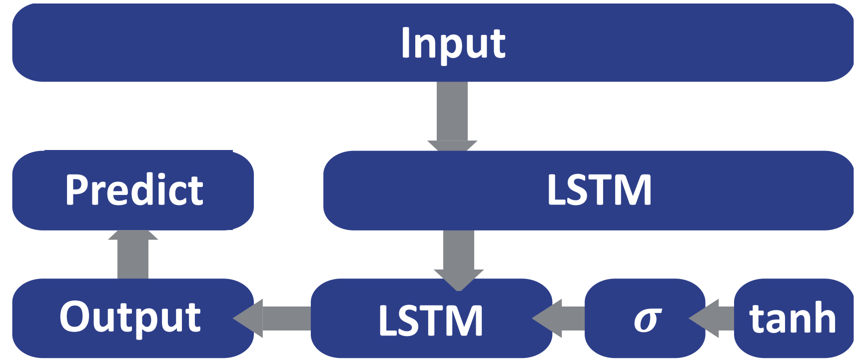
❖ Window LSTM model

- Natural LSTM networks do not necessarily give satisfactory results on segmentation.
- Most such networks receive inputs one-by-one and later predicting outputs.
- Window LSTM establish the input as *t-n* through *t-1*. (Wang & Cao, 2016)

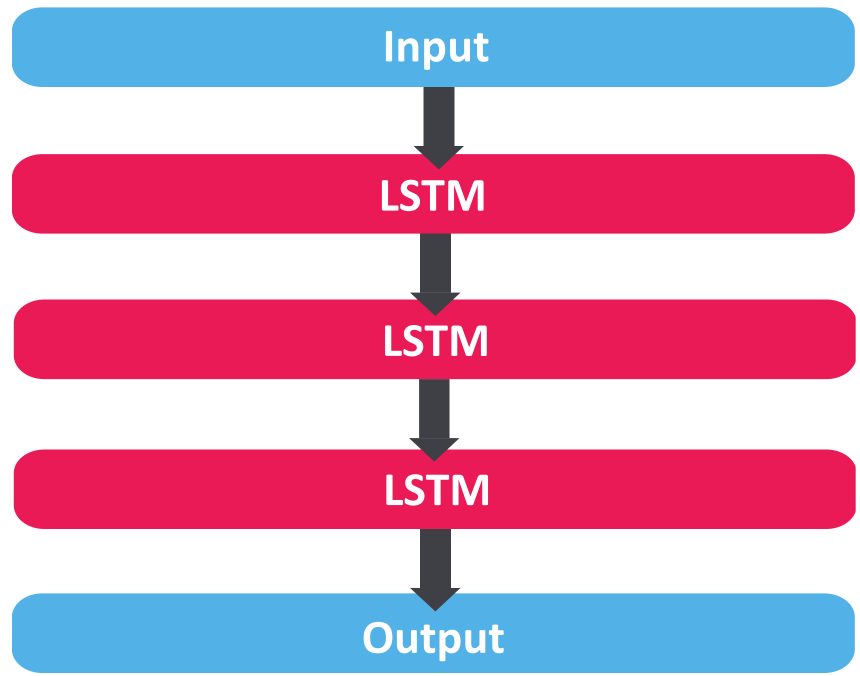
❖ Stacked LSTM model

- Building a deep RNN by stacking multiple recurrent states.
- This approach potentially allows the hidden state at each level to operate more times.
- Specific, long-term problem to adjust.

Window LSTM model

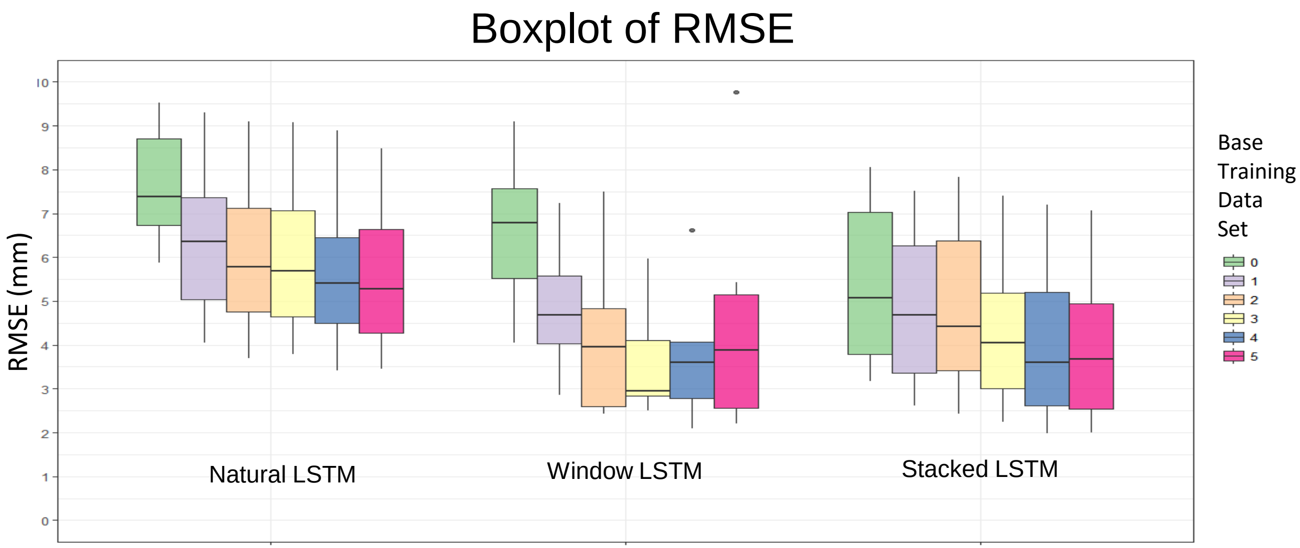


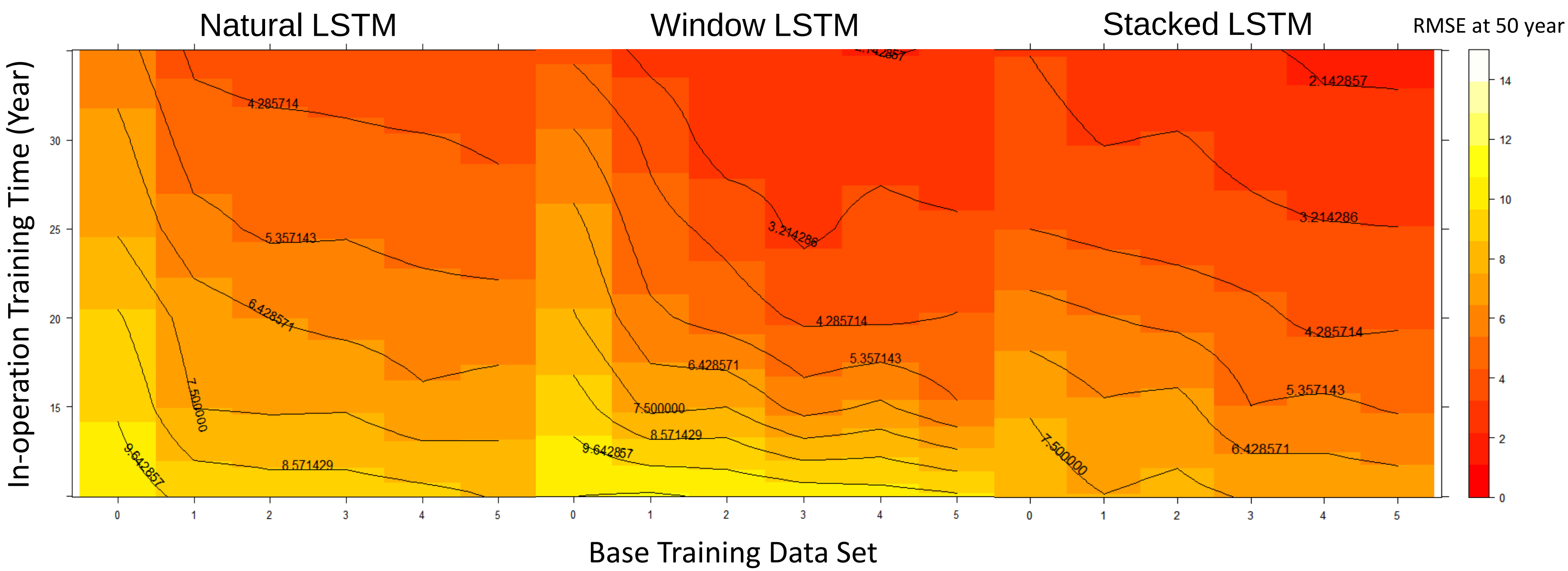
Stacked LSTM model



Numerical Results
Comparison

- It is cleary shown that the number of base training data set affects the performance of LSTM model.
- 3 LSTM models show similar trends as predicted.
- Color represents size of the error. As color becomes deeper, size of error gets smaller.



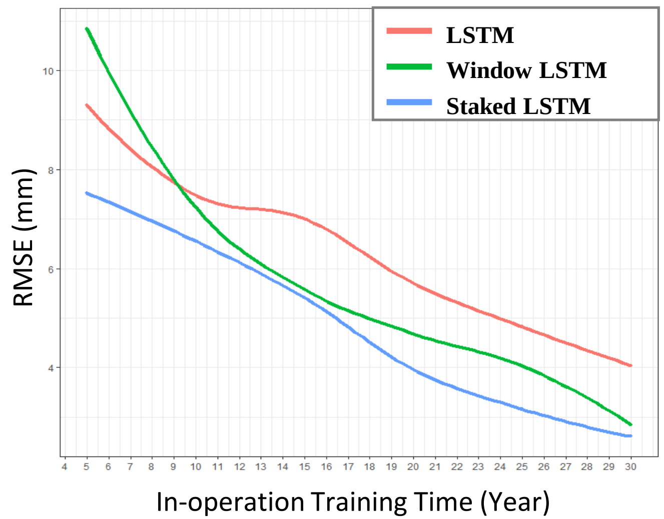


Numerical Results

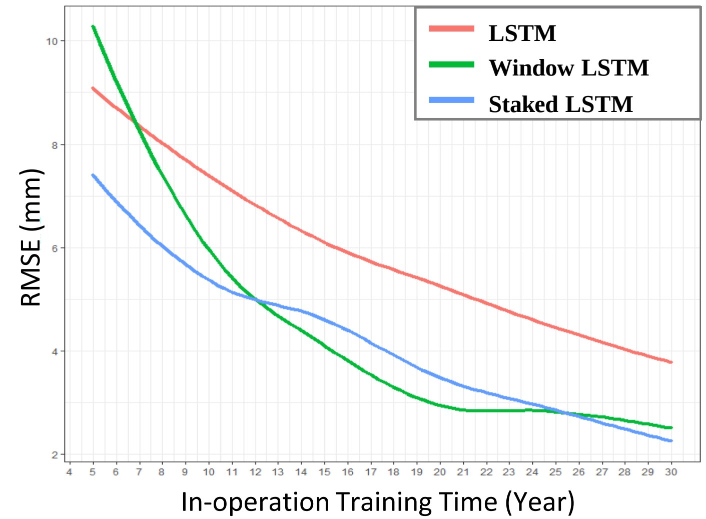
Comparison (Fixed Base Training Set and In-operation Training Time)

- Compare 3 LSTM models by fixing the base training data sets and in-operation training time.
- The results show that Window LSTM model and Stacked LSTM model are more efficient than Natural LSTM.
- In case of 5-10 years training, LSTM model has not enough time to trained.

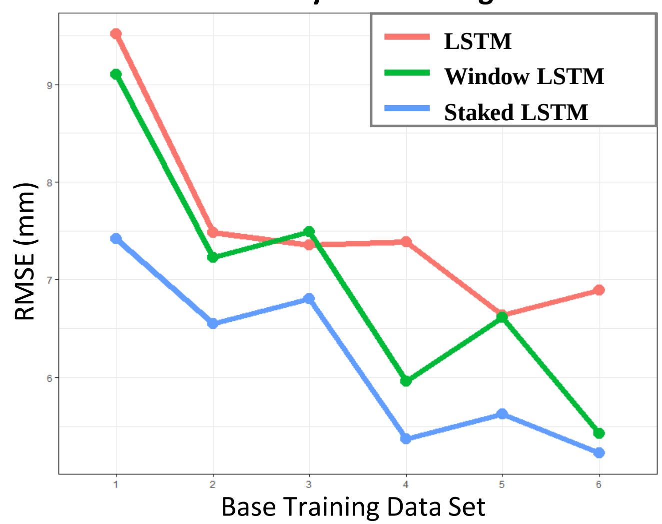
2 Base Training Data Set



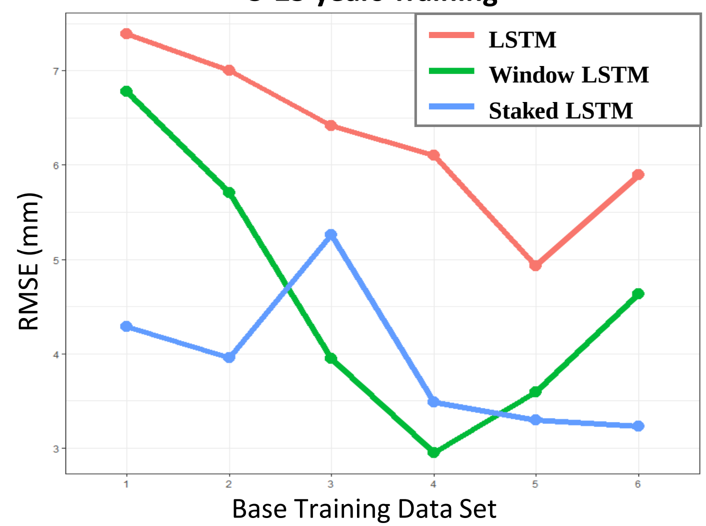
4 Base Training Data Set



5-15 years Training

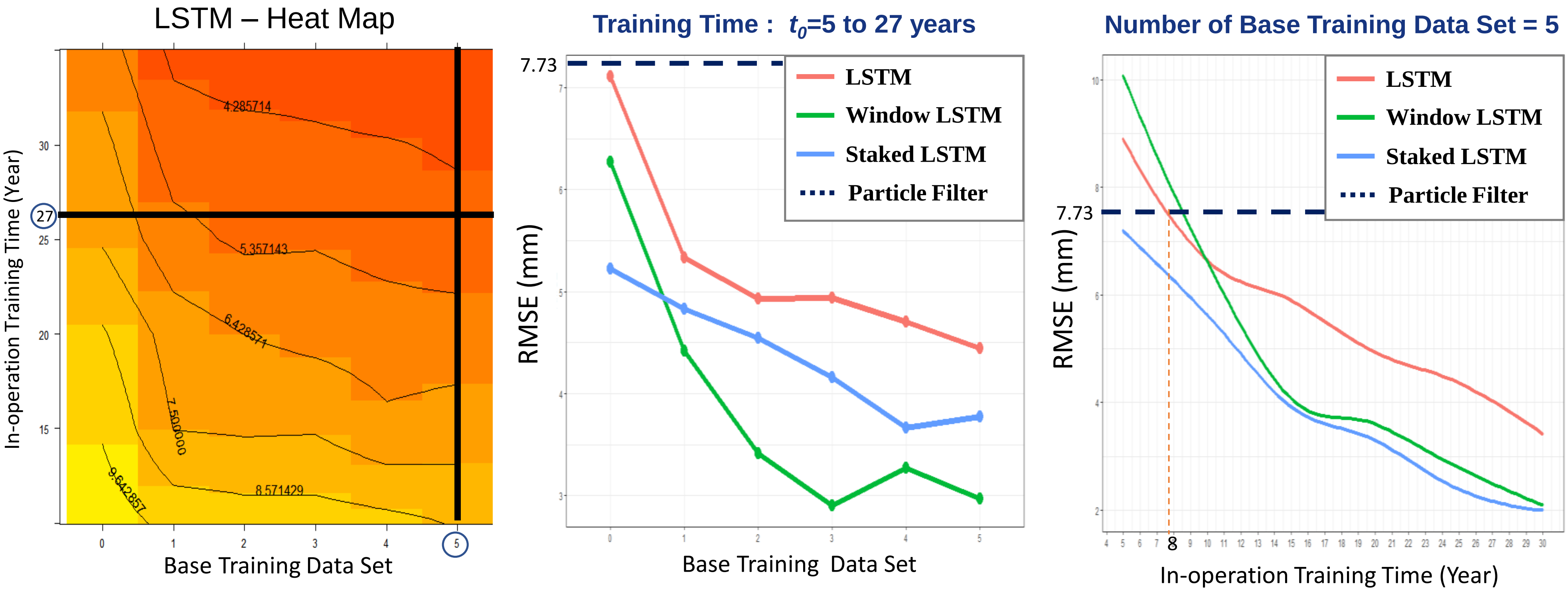


5-25 years Training



Numerical Results

Comparison (With Particle Filter)



- As the results show, average error(for 20 scenarios) of Particle Filter is **<u>7.73mm.</u>**
- To identify the results, compared with LSTM results. (Training time =27 years, Training Set=5)
- If the training time is more than 8 years, LSTM shows better performance than Particle Filter.

Summary and Conclusions

❖ Development of New Prediction Model

- The results of the several LSTM models prove that it is possible to predict the deterioration of structures with suggested error.
- Possible to decrease errors of prediction by training the LSTM models many times.
- By LSTM models, it is possible to have optimized inspection schedules that can keep risks under control and substantially reduce costs associated with operation.

❖ Future Studies

- Real-time data can demonstrate the applicability of the LSTM models.
- Measurement error can change the results of the LSTM model.
- Recurrent Neural Network(or LSTM) is Deep Learning model suitable for the multi-variable problems.

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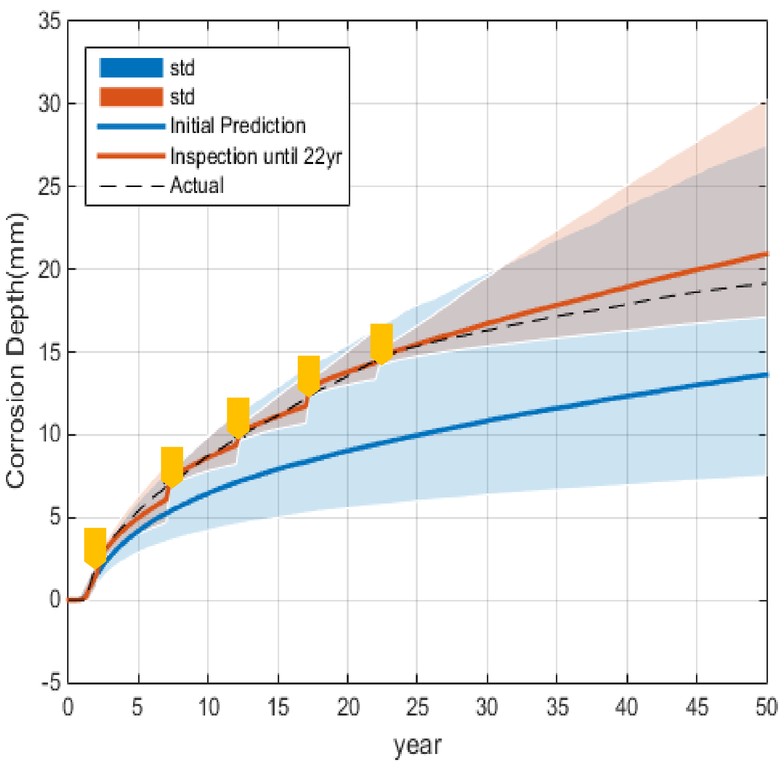
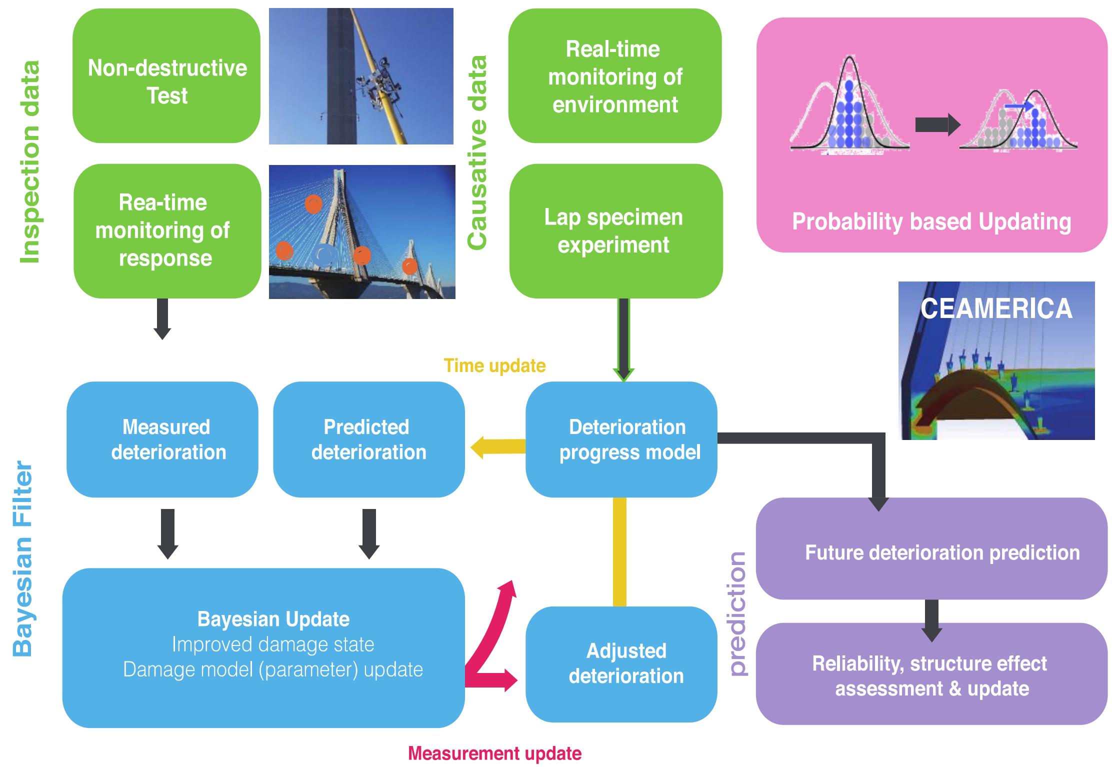
Thank You For Listening

Appendix - Particle Filter

- Full simulation based filtering method
- Monitoring/Inspection data should be used to predict future deterioration pattern
- Each Result gives 5 new parameters (V_0, t_0, α, τ, σ_o)
- For 20 scenarios in 50 year, it gives average 7.73mm error (RMSE).

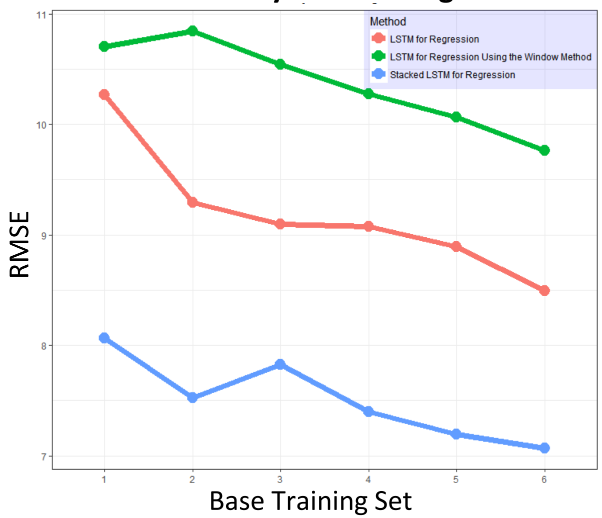




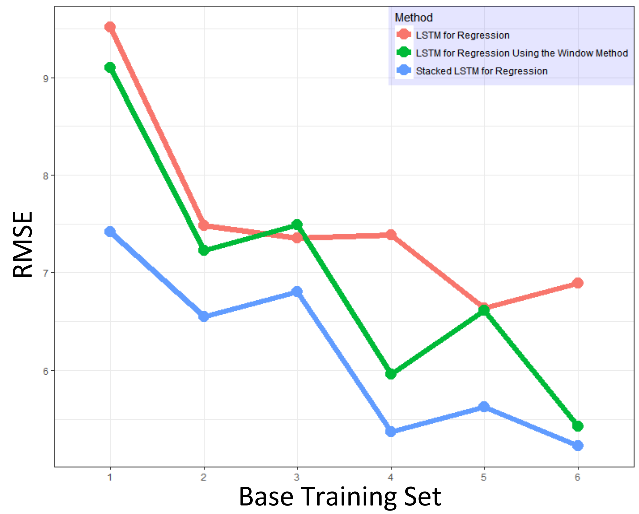
Appendix - Numerical Results

Comparison (Fixed In-operation Training Time)

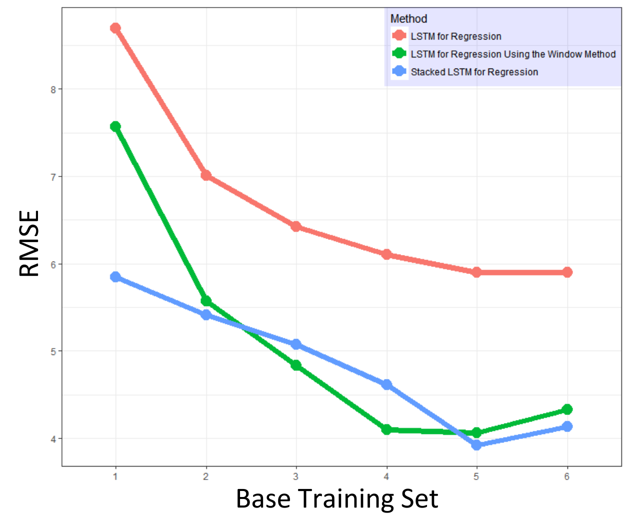
5-10 years Training



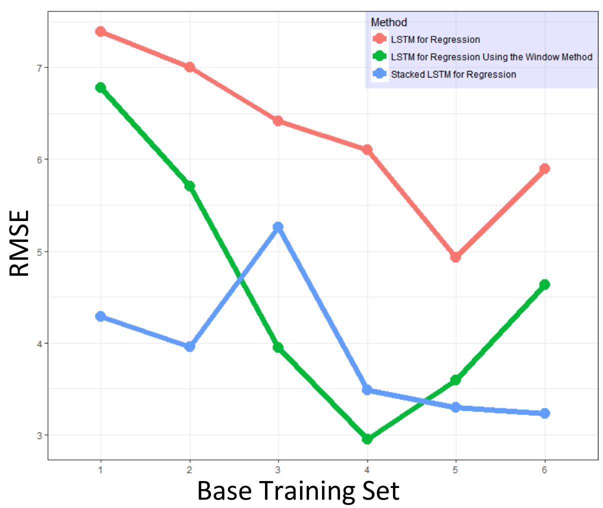
5-15 years Training



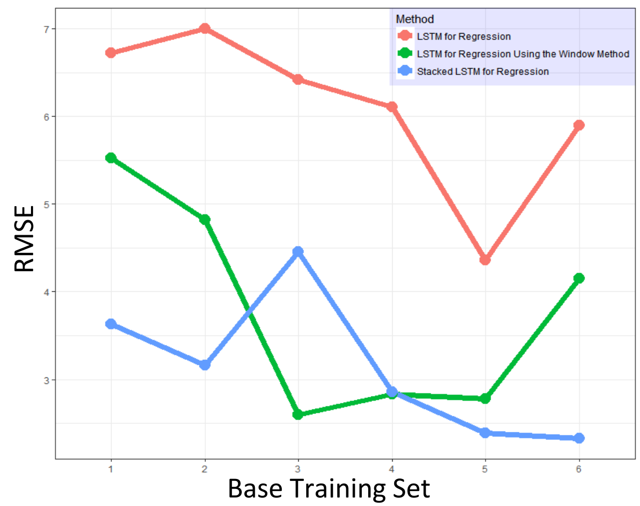
5-20 years Training



5-25 years Training



5-30 years Training



5-35 years Training