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Predicting the corrosion initiation time of fresh concrete sewers by artificial neural network

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Summary of key findings

A reliable prediction of the sewer service life is mostly determined by the progression of microbially induced concrete corrosion. This paper presents an Artificial Neural Network (ANN)-based approach for modeling the initiation of concrete corrosion processes in sewers. The ANN model was trained and validated with long-term (4.5 years) corrosion data obtained in laboratory corrosion chambers, and further verified with field measurements in real sewers across Australia. The ANN model exhibited superior performance compared against a multiple regression model also developed based on the same dataset. The model provided reasonable estimations of corrosion initiation time for the observations in Australian sewers. Furthermore, the proposed methodology holds promise to be an effective and efficient tool for the construction of analytical models associated with corrosion processes of concrete sewers. The current model can be improved and expanded adaptively by including more data measured in sewers with condition parameters spanning a greater range.

Background and relevance

In new sewers, the initiation of concrete corrosion involves both physiochemical and biological processes, which are both complicated functions of the environmental factors. Many of these processes and parameters haven't been well-studied and it would be difficult to establish a deterministic model. Artificial neural network (ANN) modelling approach was chosen for this purpose based on its merits in low requirements of detailed knowledge about the processes to be modelled.

Results

The multiple regression analysis generated an equation assuming the corrosion initiation time is linearly dependent on the explanatory variables, i.e. the location of concrete (which is scaled to numerical 1 and -1 for gas phase and partially submerged, respectively), H_2S concentration, RH and temperature (T). The regression equation is:

$$t_i = 96.34 + 1.68 * Location - 0.18 * H_2S - 0.54 * RH - 0.84 * T \tag{1}$$

The uncertainty and significance of the regression coefficients are shown in **Table 1**. All explanatory factors are significant evident by the P values for each coefficients. The intercept value is around 96 months, showing the maximum theoretical initiation time is around 8 years. Location contributes about 3.4 months of difference to the t_i, with gas phase coupons more resistant to the initiation of corrosion. Similarly, one unit increase of H_2S concentration (ppm), RH (%) and temperature (℃) induces the reduction of about 0.18, 0.54 and 0.84 month to the initiation time. The regression results align with previous observation and analysis of the corrosion development (Jiang et al., 2014). The R^2 value obtained for the multiple regression was 0.54, which implies that only 54% of the variability in the observed t_i could be captured and explained by this linear model. The fairly low R^2 value suggesting that the relationship between the predictors and t_i is not linear.

Table 1. The coefficients for the multiple regression analysis of corrosion initiation data.

Coefficients	Estimate	Std. Error	t value	P(>|t|) [1]	Significance [2]
Intercept	96.34	15.03	6.41	3.49×10^{-8}	***
Location	1.68	0.77	2.19	3.25×10^{-2}	*
H_2S	-0.18	0.05	-3.83	3.34×10^{-4}	***

RH	-0.54	0.15	-3.51	9.13×10^{-4}	***
Temperature	-0.84	0.14	-5.83	3.04×10^{-7}	***

[1] P(>|t|) is the probability value using the t-test.

[2] Significance codes based on the P value: 0-0.001: ***; 0.001-0.01: **; 0.01-0.05: *

Following the regression analysis, an ANN model was also used to analyse the same dataset. The activation function for the hidden and output layer of the ANN model was hyperbolic tangent and logistic function, respectively. Sum of squares was used as the error function for the output layer. The final structure of the ANN model has 8 neurons in the hidden layer (Figure 1). The training process was conducted using the standard backpropagation algorithm as the optimization procedure, with weights updated each time the complete training data set was considered.

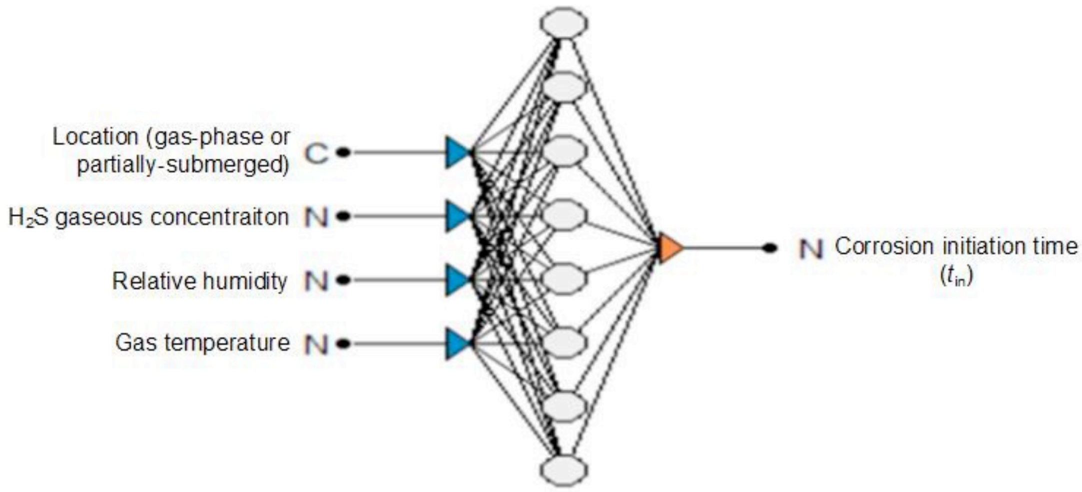

Figure 1. ANN network architecture determined for the prediction of tin.

The overall performance of the ANN model in obtaining a relationship from the training data set is high, with R=0.8291. It performs relatively well in training, validation and test, although there is a high level of scattering in the data and likely some outliers. Overall, ANN performs satisfactorily for the whole laboratory data set (R=0.8291). It must be realized that this ANN model didn't consider many other environmental factors which may contribute to the difference of the observed t_{in} values. These factors may include the fluctuation of the three controlling factors and variability in different concrete coupons. Also, the dataset supporting the ANN model is limited to the conditions investigated in the laboratory corrosion chambers. Due to its data-driven nature, the ANN model can be improved progressively by training it with more observed data.

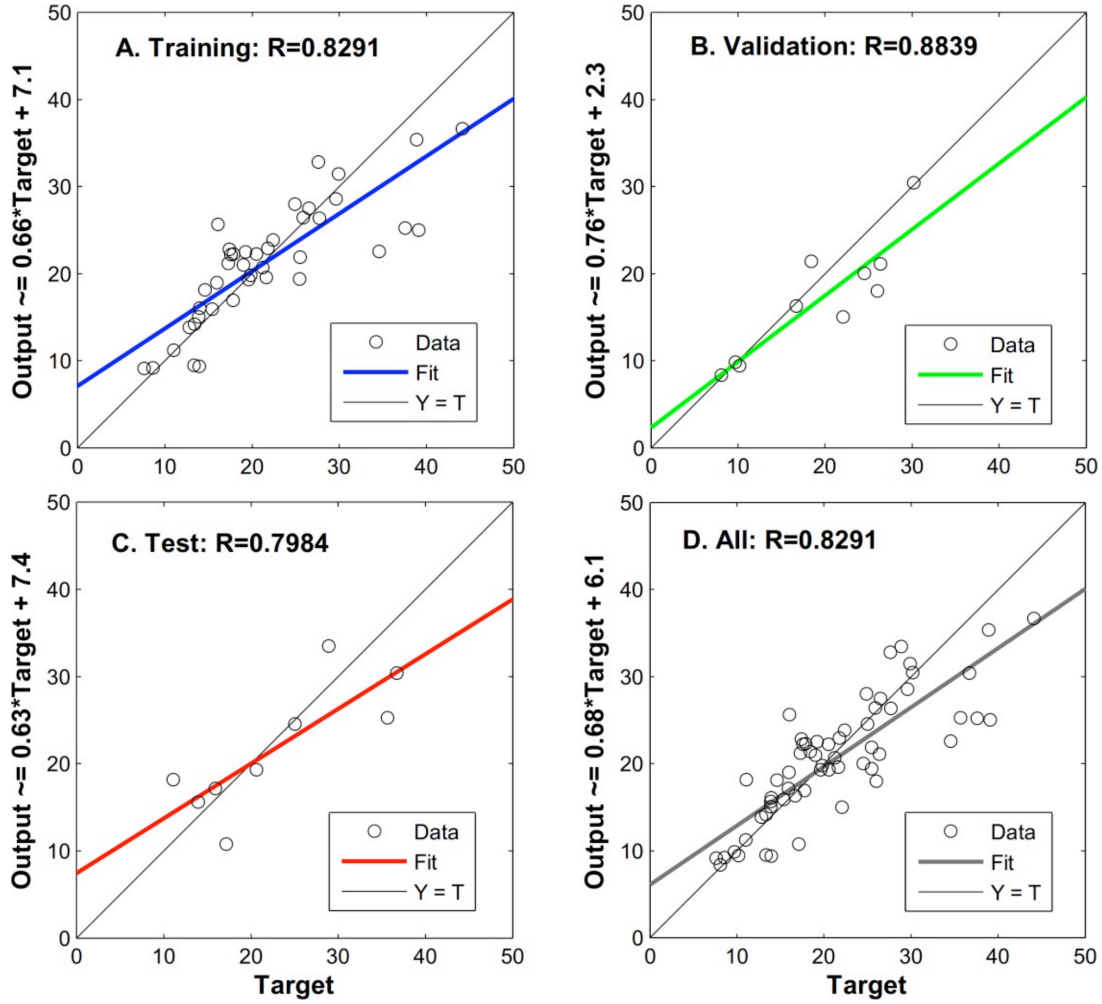

Figure 2. The performance of the ANN model using training, validation and test data set of corrosion initiation time.

After developing the ANN model to predict t_{in} based upon the laboratory data, a further step was carried out to validate its performance using field data. The corrosion initiation time t_i measured for all the field sites, including two Perth sewer and two Melbourne sewer sites, varied from site to site but fell into the range of 10 to 23 months. Also, the predictions of t_i for the field sites were compared between the ANN model and the multiple regression equation (eq. 1). **Figure 3** shows the comparison between the predicted t_i and the measured t_i for the four field sites. It is clear that the ANN model achieved reasonable accuracy for the prediction of t_i, while the multiple regression model failed to give reasonable estimates. The conditions at field sites are very different from the conditions at laboratory sewers, especially the high H_2S concentration and high temperature for Perth sewer sites (MR predicted negative t_i due to extremely high H_2S levels around 550 ppm).

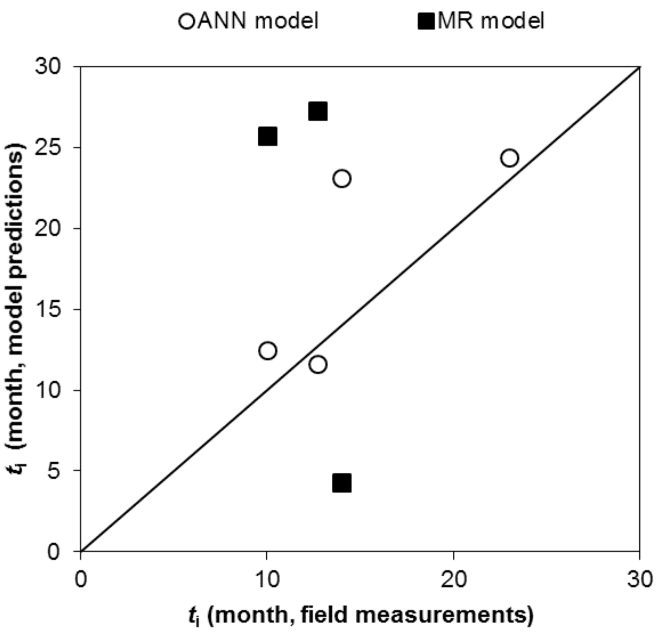

Figure 3. Validation of the ANN and multiple regression (MR) model using corrosion initiation time observed in real sewers.

Discussion

Compared to the designed lifespan of the sewer pipe (50 years or more), t_i does not constitute a significant length of time and consequently might be ignored when calculating the service lifespan of a sewer pipe. However, it is important to know t_i when a prevention strategy (such as sewer gas ventilation and chemical dosing in sewage) was in place to prevent the initiation of corrosion. The prediction capacity of t_i can be used to evaluate and optimize those corrosion prevention strategies. It would also be desirable to extend t_i during the operation of new sewer systems by controlling the sewer environmental factors. Extra life time can be added due to the delayed initiation of corrosion.

References

Jiang, G., Keller, J. and Bond, P.L. (2014) Determining the long-term effects of H2S concentration, relative humidity and air temperature on concrete sewer corrosion. Water Research 65(0), 157-169.