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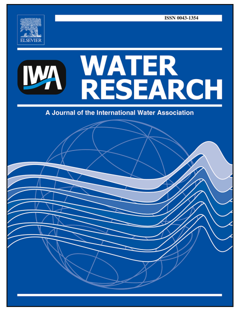

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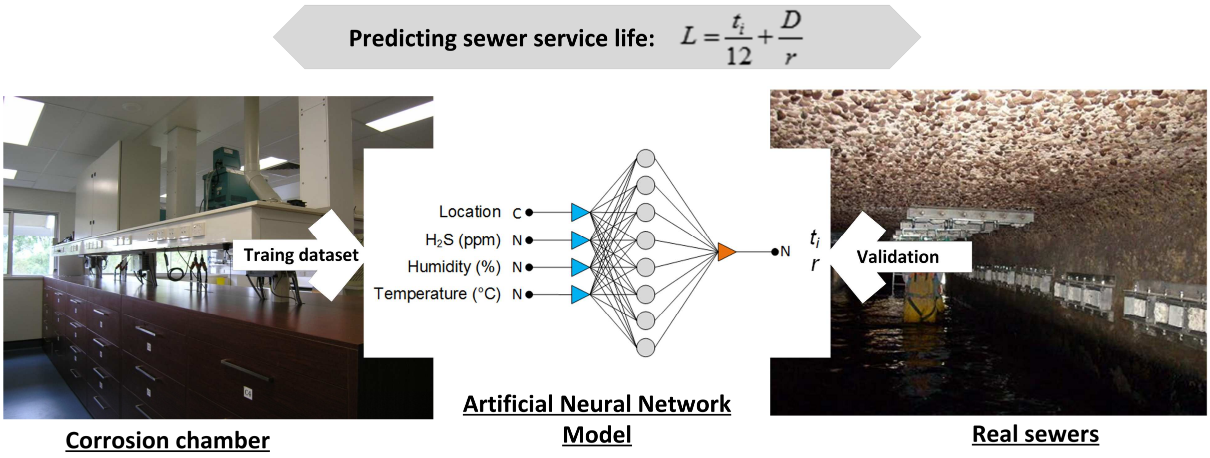

Predicting sewer service life: $L = \frac{t_i}{12} + \frac{D}{r}$
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Location C
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Validation
Corrosion chamber
Artificial Neural Network Model
Real sewers

Predicting concrete corrosion of sewers using artificial neural network

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Abstract

Corrosion is often a major failure mechanism for concrete sewers and under such circumstances the sewer service life is largely determined by the progression of microbially induced concrete corrosion. The modelling of sewer processes has become possible due to the improved understanding of in-sewer transformation. Recent systematic studies about the correlation between the corrosion processes and sewer environment factors should be utilized to improve the prediction capability of service life by sewer models. This paper presents an artificial neural network (ANN)-based approach for modeling the concrete corrosion processes in sewers. The approach included predicting the time for the corrosion to initiate and then predicting the corrosion rate after the initiation period. 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 trained model estimated the corrosion initiation time and corrosion rates very close to those measured in Australian sewers. The ANN model performed better than a multiple regression model also developed on the same dataset. Additionally, the ANN model can serve as a

prediction framework for sewer service life, which can be progressively improved and expanded by including corrosion rates measured in different sewer conditions. Furthermore, the proposed methodology holds promise to facilitate the construction of analytical models associated with corrosion processes of concrete sewers.

Key words

Sewer; corrosion; concrete; hydrogen sulfide; artificial neural network; multiple regression model

Nomenclature

ANN	Artificial Neural Network
GP	Gas-phase
MICC	Microbially induced concrete corrosion
MR	Multiple regression
PS	Partially-submerged
SOB	Sulfide-oxidizing bacteria
RH	Relative humidity

1 Introduction

Sewer networks established through continuous public investment are important infrastructure supporting modern urban living. With estimated values of one trillion dollars in the USA and $35 billion in Australia these are valuable assets, however, sewers are degrading at a very high rate, in many cases due to microbially induced concrete corrosion (Brongers et al., 2002). The annual total cost of corrosion within the water and wastewater infrastructure is reported to be US$ 36 billion in USA (Koch et al., 2002). Corrosion causes the loss of concrete mass and structural capacity, eventually leading to ultimate structural collapse. The rehabilitation and replacement of damaged sewers is costly, in the USA alone this was estimated to be around $14 billion per year (Brongers et al., 2002). This cost is expected to increase as the aging infrastructure continues to fail (Alexander et al., 2013; Boulos and Walker, 2015; Sydney et al., 1996; US EPA, 1991).

To alleviate and control corrosion problems in concrete sewers, various technologies have been employed to remove or reduce hydrogen sulfide levels in the sewage or sewer air. This includes removal from sewage by dosing with chemicals such as nitrates or iron salts to reduce the formation or emission of H_2S (Gutierrez et al., 2008; Jiang et al., 2011; Jiang et al., 2013; Jiang and Yuan, 2013; Zhang et al., 2009) or removal of H_2S from sewer air (Sivret and Stuetz, 2010). Other technologies include construction of new sewers with corrosion-resistant pipe materials or to repair corroded concrete surfaces with corrosion resistant layers (De Muynck et al., 2009; Haile et al., 2010; Hewayde et al., 2007).

It is thus critical to accurately estimate the sewer service life for the purpose of planning sewer maintenance and rehabilitation and for evaluating and optimizing the effectiveness of various control technologies. The most direct indicator for the effectiveness of these various technologies should be the sewer service life (L, year), which is determined by the time for corrosion to initiate (t_i, month) and the corrosion rate (r, i.e. concrete depth lost over time, mm/year) (equation 1).

$$L = \frac{t_i}{12} + \frac{D}{r} \qquad (1)$$

Where D is the concrete depth (mm) that can be sacrificed before the end of sewer service life. This bilinear corrosion model was proposed based on sewer concrete losses measured in the field (Wells and Melchers, 2014). However, the model was not parameterized for application to different sewer conditions due to it being based on very limited field data.

Existing sewer process models mainly focused on the modelling of hydrogen sulfide production and wastewater characteristics in sewer networks (Hvitved-Jacobsen et al., 2013; Sharma et al., 2014; Sharma et al., 2013; Sharma et al., 2008; Vollertsen et al., 2008; Vollertsen et al., 2011; Vollertsen et al., 2015). These models lack a thorough approach for the estimation of corrosion rate based on the simulated profile of hydrogen sulfide and other environmental factors. The well-known Pomeroy model was used to calculate the deterioration rate of concrete sewer pipes (Pomeroy, 1990). This empirical model was widely used although it fails to take into account recent findings of the corrosion process and associated impacting factors. It is recently shown that both the corrosion initiation time and corrosion rate depend on various sewer environmental factors that include the H_2S concentration, relative humidity and temperature (Jiang et al., 2014a; Jiang et al., 2015). Additionally, it was recently discovered that the corrosion development can be facilitated by internal cracking which is caused by the formation of corrosion products that include iron oxides precipitating in concrete (Jiang et al., 2014b; Monteny et al., 2000; Parande et al., 2006).

Another hurdle to the implementation of equation 1 is the absence of a model estimating the initiation time for corrosion (t_i). The corrosion initiation involves a combination of physical, chemical and biological processes. The transition of the highly alkaline fresh concrete surface of the pipe to a more microbe habitable environment occurs by acidification through carbonation (by CO_2) and H_2S dissociation during the initial stages of corrosion (Joseph et al., 2012). This is facilitated by the physicochemical conditions in gravity sewers through adequate water availability (due to high relative humidity), high concentrations of carbon dioxide, high concentrations of H_2S and lowered surface pH (Wei et al., 2014). As the surface pH lowers towards neutrality various sulfide-oxidizing bacteria (SOB) will populate the corrosion layer and produce sulfuric acid (Cayford et al., 2012; Okabe et al., 2007; Santo Domingo et al., 2011).

Recently a model was developed with H_2S concentration as the key parameter and this was validated with laboratory data for the concrete corrosion of the crown area in sewer pipes (Jiang et al., 2014a). However, due to the difficulty in using deterministic models to simulate the complex processes involved in corrosion, black-box type models can be used to obtain predictions with reasonable accuracy. The artificial neural network (ANN) modelling approach, inspired by biological neural systems, is an effective modelling tool (Hsu et al., 1995). ANN models ‘learn’ the patterns of the underlying process from past data and generalize the gained ‘knowledge’ (or mathematical relationships between input and output data) to predict an output given a new set of input variables from the problem domain. It has the potential to predict any complex system with high precision provided its architecture and parameters are properly set. ANN models have found many different applications including data mining, pattern recognition, clustering analysis and predictive modelling. In the field of corrosion, ANN is successfully used for the prediction of carbon steel corrosion when exposed to the atmosphere or to crude oil (Kenny et al., 2009; Pintos et al., 2000; Rebak, 2005).

This study proposes a data-driven approach based on ANN for the estimation of both corrosion initiation time (t_i) and corrosion rate (r). As discussed, the two parameters vary from site to site due to the local environmental conditions. Our previous laboratory investigations cover the development and established stages of sewer corrosion, and provide extensive data evaluating the effect of three controlling factors: H_2S concentration, gas temperature and relative humidity (Jiang et al., 2014a; Jiang et al., 2015). Those studies also investigated the effect of locations within the sewer on corrosion, exposing concrete to either the sewer atmosphere (simulating the crown) or by partially-submerging it in sewage (simulating the sewer tidal region at the sewage/air interface). Consequently, we utilized this extensive dataset to build ANN models to predict t_i and r, which can be used to estimate the service life for a specific sewer. The performance and application of the proposed ANN model was further evaluated by comparison with a classical regression model and with observations in real sewer sites across Australia.

2 Material and Methods

2.1 Long-term corrosion tests in laboratory chambers

Thirty-six identical corrosion chambers were constructed to achieve controlled environments simulating that of real sewers (Jiang et al., 2014a). The controlled factors include combinations of three gas-phase temperatures (17 °C, 25 °C and 30 °C), two levels of relative humidity (RH) (100% and 90%) and six H_2S levels (0 ppm, 5 ppm, 10 ppm, 15 ppm, 25 ppm and 50 ppm). Each chamber contained 2.5 L of domestic sewage that was collected from a local sewer pumping station and replaced every two weeks.

Concrete coupons were prepared from fresh and precorroded sewer pipes to investigate the corrosion initiation and the active corrosion respectively. The fresh concrete coupons were prepared from a new sewer pipe (1.2 m diameter and 0.07 m thickness) obtained from a sewer pipe manufacturer (HUMES, Sydney, Australia). The precorroded coupons were prepared from corroded concrete sewer slabs obtained from Sydney Water Corporation, Australia. One of the original surfaces of the coupons, i.e. the internal surface of the pipe, was designated as the surface to be exposed to H_2S. Part of the coupons were embedded as pairs (1 fresh + 1 precorroded) in stainless steel frames using epoxy (FGI R180 epoxy & H180 hardener) with the steel frame providing a reference point for determining the change in thickness due to corrosion (Jiang et al., 2014b).

For each chamber, eight pairs of enclosed coupons were exposed to the gas phase. These gas-phase concrete coupons represent the sewer pipe crown, a location which is highly susceptible to sulfide induced corrosion (Mori et al., 1992; Vollertsen et al., 2008). Another eight pairs of bare coupons (8 fresh + 8 precorroded) were partially submerged (approx. 20-30 mm) in the wastewater simulating the concrete sewer pipe near the water level, which is also a region of high corrosion activity.

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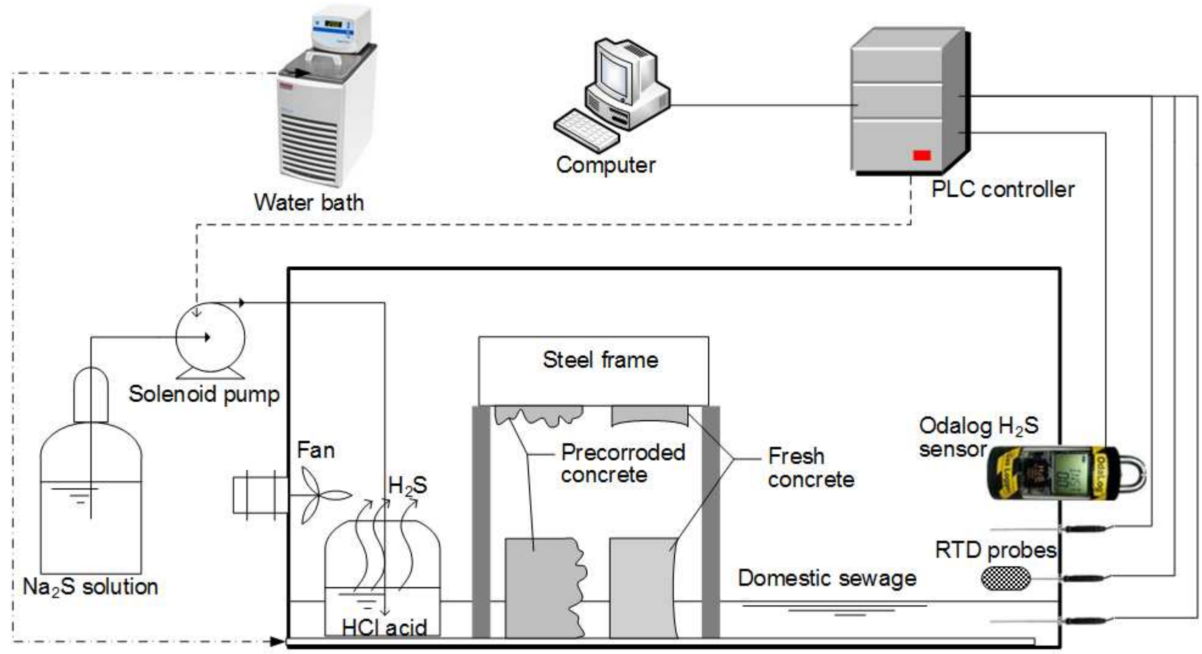

Figure 1. Side view of a corrosion chamber with H_2S concentration, relative humidity and gas temperature controlled by PLC. The orientation of the gas-phase and partially-submerged coupons is shown.

The corrosion chambers were operated for up to 54 months since December 2009. Periodically, at intervals between 6-10 months, one set of coupons (one pair of gas-phase coupons and one pair of partially-submerged coupons) were retrieved from each corrosion chamber for detailed analysis. A standard step-by-step procedure of methods was employed to measure surface pH, followed by sampling for sulfur species and then photogrammetry analysis (thickness change). The detailed sampling and analysis procedures were described previously (Jiang et al., 2014a).

The corrosion initiation time, t_i, was determined as the time to reach a detectable level of sulfate on the fresh concrete surface assuming a linear increase of sulfate production with time (Jiang et al., 2015). The mass loss data of precorroded coupons were used to calculate the corrosion rate as the thickness change per year, i.e. mm/year.

2.2 Long-term corrosion tests in real sewers

Concrete corrosion was studied in real sewer systems to quantify corrosion occurring in working Australian sewers under a range of environmental and operating conditions. Six sewer sites were chosen in three cities, i.e. Sydney, Melbourne and Perth in Australia. The choice of three cities and two sites in each city enabled the study of different temperatures and different H_2S levels. Concrete coupons were fixed into the sewers as described (Wells and Melchers, 2015) and then recovered approximately every 6 months in the early stages of the trial and yearly in the later stages. The retrieved coupons were analyzed similarly to the laboratory coupons for measurement of surface pH, sulfur compounds in the corrosion layer and the mass loss due to corrosion. Details of the study were reported by Wells and Melchers (2015) and the corrosion initiation time and corrosion rate determined in real sewers were used to validate the ANN model in this study.

2.3 Statistical data analysis

Statistical Analysis of the data was performed using R (ver 3.03, http://www.R-project.org/). Multiple linear regression analysis was performed on the corrosion initiation time and corrosion rate, with explanatory factors including H_2S concentration, relative humidity and temperature. The coefficients for each of the explanatory factors were determined together with the standard error. The non-significant contributing factors (P<0.05) were excluded in a step by step manner to achieve a minimum adequate model. The regression models were then used to predict corrosion initiation times and corrosion rates for the conditions in the laboratory and field sewers, As well, some sewer examples from the literature were used for these predictions. The performance of the regression models were compared to the ANN based model outputs.

2.4 Artificial neural network modelling

Basic structure of an artificial neural network model is composed of three layers, i.e. input, hidden, and output layer. The neural network modelling process used in this study may be described in four steps: (i) pre-processing of the original data set (determination of t_i and r from experimental data and identification of outliers); (ii) partitioning of the pre-processed data set into learning, validation and test sets; (iii) ANN model architecture setting, learning and testing; and (iv) validation using field data.

In the first stage the pre-processed data set was sorted by experimental factors (the location of concrete coupons, H_2S concentration, gas temperature and relative humidity) and the learning, validation, and test data were constructed using a randomization procedure. The percentage of observations per data set were assigned to be 70%, 15% and 15%, for the learning, validation and test sets, respectively. The learning data set was used to train the ANN. The validation data set was used in conjunction with the learning data set to determine when to stop the learning process such that the resulting model exhibited good generalization properties. The test data set allows the assessment of the prediction capabilities of the ANN model. The ANN was evaluated using as performance criteria mean square error and residual distributions over the learning and test data sets.

Step 3 involves the ANN architecture setting and optimization. The ANN model we designed with three layers: one input layer, one hidden layer and one output layer. Generally speaking one hidden layer should be suffice for most practical problems, thus only one hidden layer was used in this study. This was verified by comparing the performance against models with more than one hidden layer. The nodes for the ANN input and output layer were set by the number of input factors (one category and three numerical, shown in Figure 2) and the number of variables to be predicted (t_i or r), respectively. The input layer includes four nodes that represent the four influencing factors of sewer corrosion environment: location of the sewer pipe, H_2S concentration, gas temperature and relative humidity. The number of nodes in the hidden layer was established before the ANN model architecture was completed. An exhaustive search was conducted to determine the optimal number of neurons in the hidden layer using Alyuda NeuroIntelligence ver 2.2. The best architecture was then constructed for the training and validation analysis using Matlab R2014a.

3 Results and Discussion

3.1 Prediction of the initiation of corrosion - t_i

An equation was generated from the multiple regression (MR) analysis to predict the concrete corrosion initiation time (equation 2). This assumes the corrosion initiation time is linearly dependent on the explanatory variables, i.e. the location of concrete, H_2S concentration, RH and temperature (*T*).

$$t_i = 96.34 + 1.68 * Location - 0.18 * H_2S - 0.54 * RH - 0.84 * T \qquad (2)$$

The uncertainty and significance of the regression coefficients were determined and all explanatory factors were significant as evident by the *P* values for each coefficient (Table 1). The intercept value of around 96 months, indicates 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 (°C) causes reductions of about 0.18, 0.54 and 0.84 months to the initiation time respectively. The regression results align with previous observation and analysis of the corrosion development (Jiang et al., 2015). 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 suggests that the relationship between the predictors and t_i is unlikely linear.

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

Coefficient	**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 represent P values of: 0-0.001: ***; 0.001-0.01: **; 0.01-0.05: *

Following the regression analysis, an ANN model was used to analyse the same dataset. The final structure of the ANN model has 8 neurons in the hidden layer (Figure **2**). The activation functions for the hidden and output layers of the ANN model were hyperbolic tangent and logistic function, respectively. Sum of squares was used as the error function for the output layer. 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.

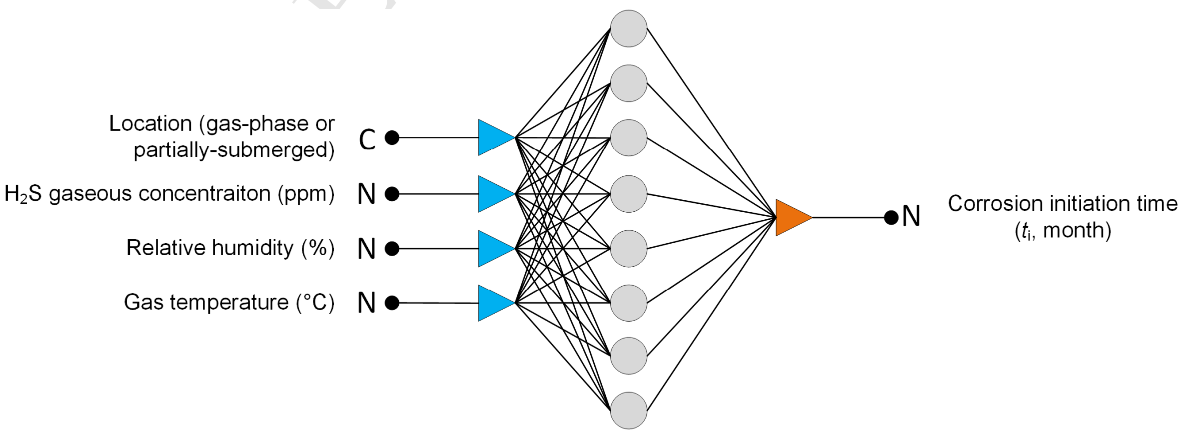

Figure 2. The network architecture of the ANN model for the prediction of t_i.

The ANN model obtained a good relationship from the training data, with an R value of 0.8291 (Figure 3A), and it performed relatively well in the validation and testing, although there is a high level of scattering of the data and likely some outliers (Figures 3B and 3C). Overall, the ANN performs satisfactorily for the whole laboratory data set (Figure 3D). It must be realized that this ANN model did not consider other environmental factors which may affect t_i values. These factors may include fluctuations of the three controlling factors and variability in different concrete, such as aggregate levels. 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.

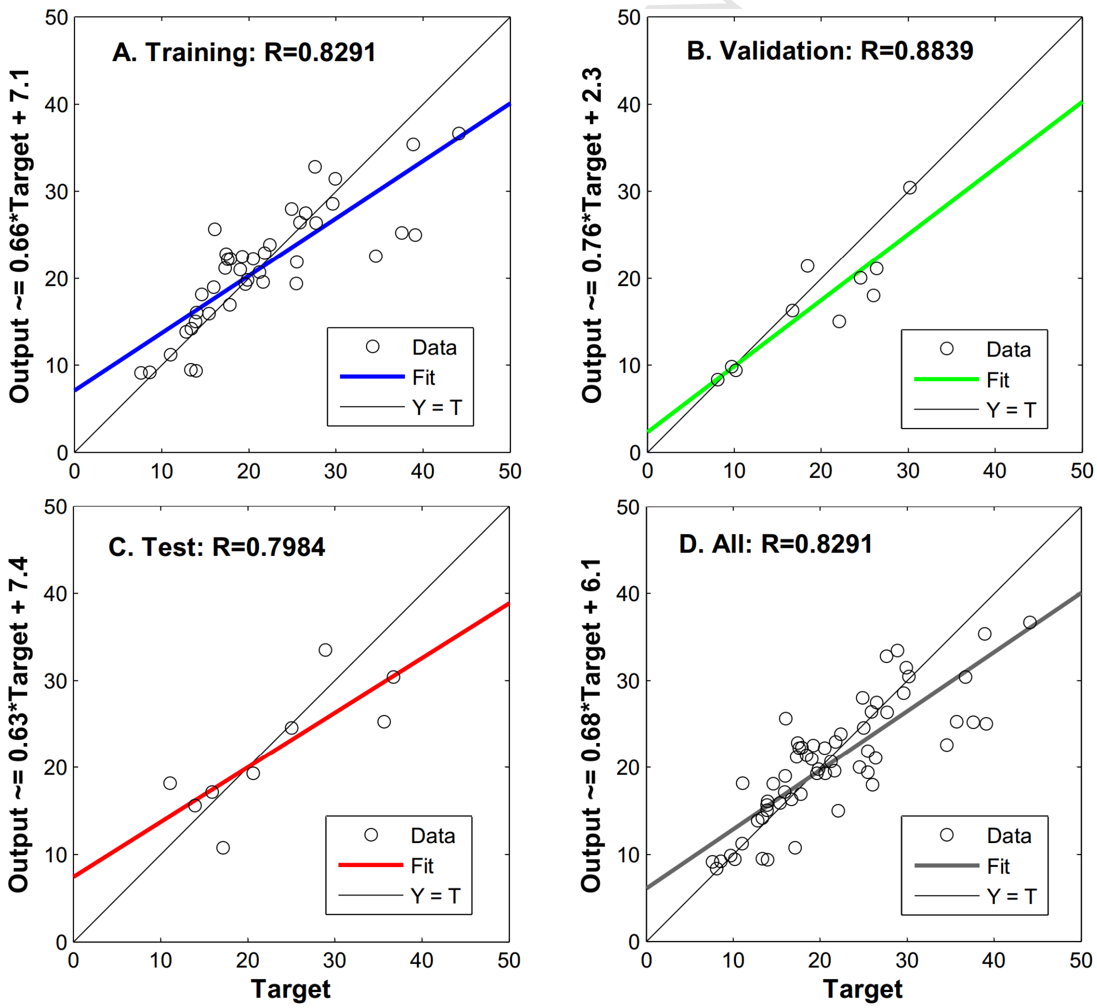

Figure 3. Outputs of the ANN model using training (A), validation (B), test (C) and the complete (D) data sets for the corrosion initiation time. The concrete corrosion initiation times were determined from coupons exposed to conditions simulating environments in sewers using laboratory corrosion chambers.

After developing the ANN model to predict t_i based upon the laboratory data, a further step was carried out to vadiate its performance using field data. The corrorion initiation time t_i measured for all the field sites, including two Perth sewers and two Melbourne sewers, varied from site to site but were in the range of 9 to 24 months. Also, we compared the predictions of t_i for the field sites between the ANN model and the multiple regression equation (eq. 1) (Figure 4). In 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 (Figure 4). Some conditions at the field sites were far beyond the ranges for those in the laboratory corrosion chambers (Wells and Melchers, 2015). In particular, the Perth sewer site had very high H_2S concentrations, up to 830 ppm, and high temperatures, and in that situation the MR model predicted a negative t_i.

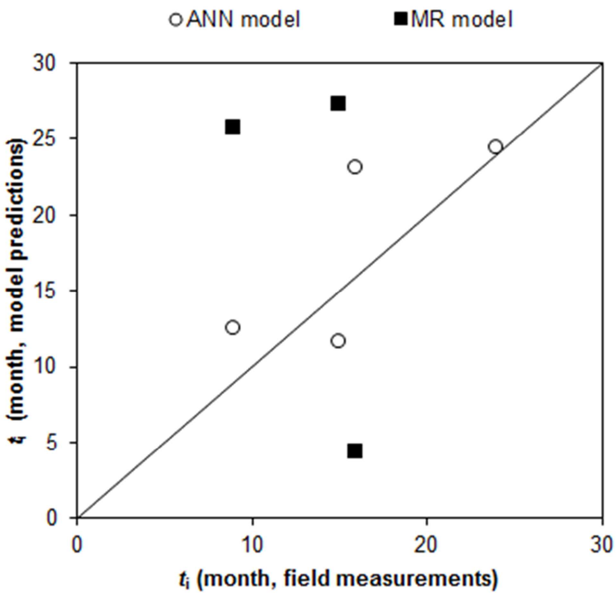

Figure 4. Validation of the ANN and multiple regression (MR) model using corrosion initiation time observed in real sewers.

Compared to the designed lifespan of the sewer pipes (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, t_i is important when a prevention strategy, such as sewer gas ventilation and chemical dosing in sewage, is in place to prevent the initiation of corrosion. For example, the CO_2 levels can be greatly reduced by ventilation from 0.2-1.2% in sewers to the atmospheric level (0.04%) and thus the carbonation of concrete. 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. The service time of the sewer can be extended by delaying the initiation of corrosion.

3.2 Prediction of corrosion rate - *r*

The linear equation for corrosion rate generated by multiple regression was determined (Eq. 3). However, the coefficients for RH and temperature are shown to be insignificant (Table 2). Further analysis using back selection was carried out to obtain the minimum adequate model (Eq. 4). From the regression coefficients for location (0.45), it can be inferred that the difference of corrosion rates for a sewer pipe in the gas phase (crown) and the partially submerged (water line) area is about 0.9 mm/year. Also, an increase of H_2S by 10 ppm will cause about 0.28 mm/year increase of corrosion rate. However, it is evident this regression model over-predicts corrosion rates when the H_2S concentration is low, e.g. 0.6-1.5 mm/year of corrosion is estimated when H_2S is at 0 ppm. The R^2 value obtained for the multiple regression was 0.59, which implies that only 59% of the variability in the observed r was captured and explained by this linear model.

$$r = -0.63 - 0.45 * Location + 2.82\times10^{-2} * H_2S + 8.69\times10^{-3} * RH + 1.57\times10^{-2} * T \qquad (3)$$

$$r = 1.03 - 0.45 * Location + 2.82\times10^{-2} * H_2S \qquad (4)$$

Table 2. The coefficients for the multiple regression analysis of corrosion rate data.

Coefficients	Estimate	Std. Error	t value	P(>|t|) [1]	Significance [2]
			Full model		
Intercept	-0.17	1.26	-0.138	0.891	
Location	-0.45	0.064	-7.046	1.25×10^{-9}	***
H_2S	2.82×10^{-2}	3.89×10^{-3}	7.252	5.36×10^{-10}	***
RH	8.69×10^{-3}	0.013	0.676	0.501	
Temperature	1.57×10^{-2}	0.012	1.31	0.195	
			Minimum adequate model		
(Intercept)	1.03	0.0938	10.982	$<2\times10^{-16}$	***
Location	-0.45	0.0644	-7.037	1.14×10^{-9}	***
H_2S	2.82×10^{-2}	0.0039	7.243	4.82×10^{-10}	***

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

[2] Significance codes represent P values: 0-0.001: ***; 0.001-0.01: **; 0.01-0.05: *

To improve the prediction of corrosion rate an ANN model was developed in a similar approach used for the prediction of corrosion initiation (section 3.1). The best architecture determined by exhaustive searching, based on R-square, has one input layer (4 inputs including location, H_2S concentration, RH and temperature), one hidden layer (9 nodes), and one output layer for the output variable of corrosion rate (r). The model was trained using the 72 sets of corrosion data obtained in the laboratory corrosion chamber.

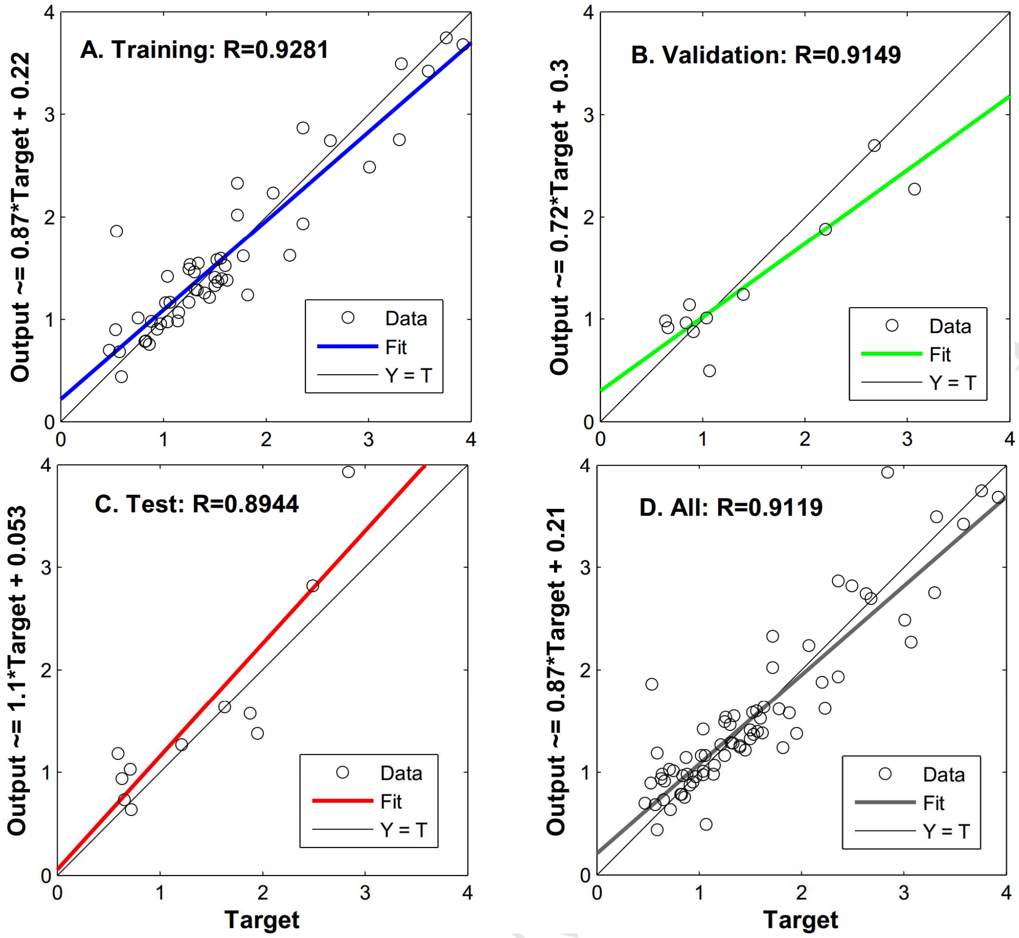

Figure 5. The outputs of the ANN model using training (A), validation (B) and test (C), and the complete (D) data sets of corrosion rates. The concrete corrosion rates were determined from coupons exposed to conditions simulating environments in sewers using laboratory corrosion chambers.

The ANN model showed excellent performance in both training, validation and test, with an overall R=0.9119 (Figure 5D). This indicates that the model established a clear relationship between the environmental factors and the corrosion rate. The trained ANN model was further validated using corrosion rates measured in four Australian sewer sites and those in literature reviewed by Wells and Melchers (2015). The ANN model demonstrated accurate predictions of corrosion rates for most sewer sites, while under-predicting the corrosion rates of two sites (Figure 6). The under-predicted sites had corrosion rates of up to 11 mm/year, which is nearly 3 times the maximum rates measured in the laboratory corrosion chambers.

Likely, those low predictions occurred because the ANN was trained solely on the laboratory data. To improve the ANN model, the field and literature dataset was included in the model training process. It is clear this significantly improved the ANN's capability in predicting the higher corrosion rates (Figure 6). The MR model did show promising performance especially for corrosion rates lower than 4 mm/year. Thus, in certain circumstances it might be very useful to use such a simple model (Eq. 4) to make reasonable predictions of corrosion rates. However, the ANN model is a more sophisticated predictive tool with higher accuracy that can be applied to a wider range of conditions.

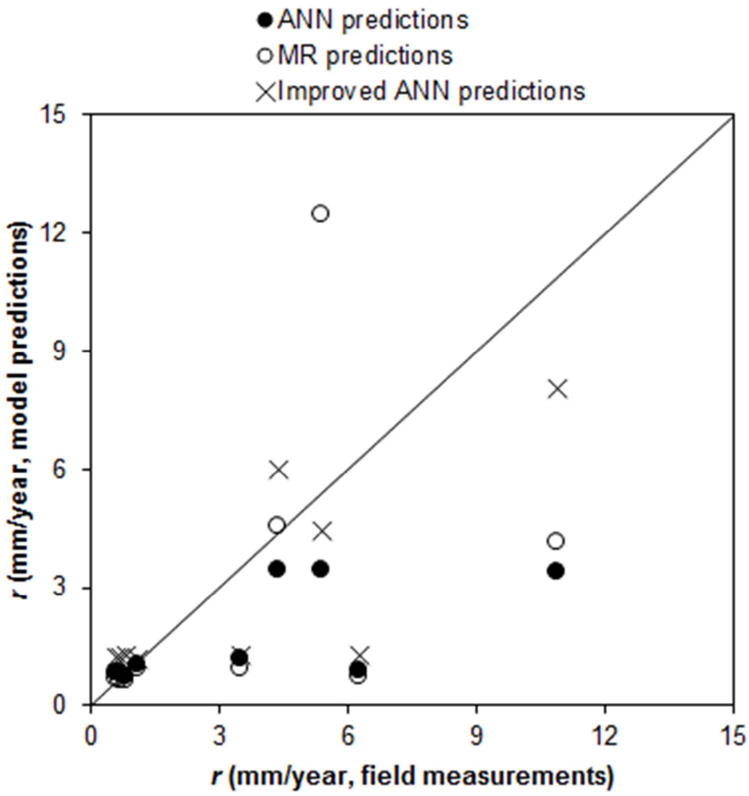

Figure 6. Validation of the ANN and multiple regression (MR) models using corrosion rates observed in real sewers. The ANN predictions were improved by including corrosion rates observed in real sewers in the model training process.

3.3 Sensitivity and uncertainty of the prediction

Sensitivity analysis conducted on the trained neural network revealed the effects of sewer environmental factors on both t_i and r (Figure 7A-F). The neural network models, established in section 3.1 and 3.2, separated the effects of the variables and simulated the effects of each individual factor (Figure 7A-F). In most cases nonlinear responses were evident, except for the semi-linear change of t_i to RH and temperature (Figure 7B and C). Also, it was seen that the sensitivity of t_i to environmental factors are in the order of H_2S > Temperature > RH, for the range of factors used in the lab corrosion chambers. The corrosion rate, it seems was most sensitive to the H_2S concentration (Figure 7D). These sensitivity analyses confirm previous findings identifying controlling factors for the initiation period and for the active corrosion stage (Jiang et al., 2014a; Jiang et al., 2015).

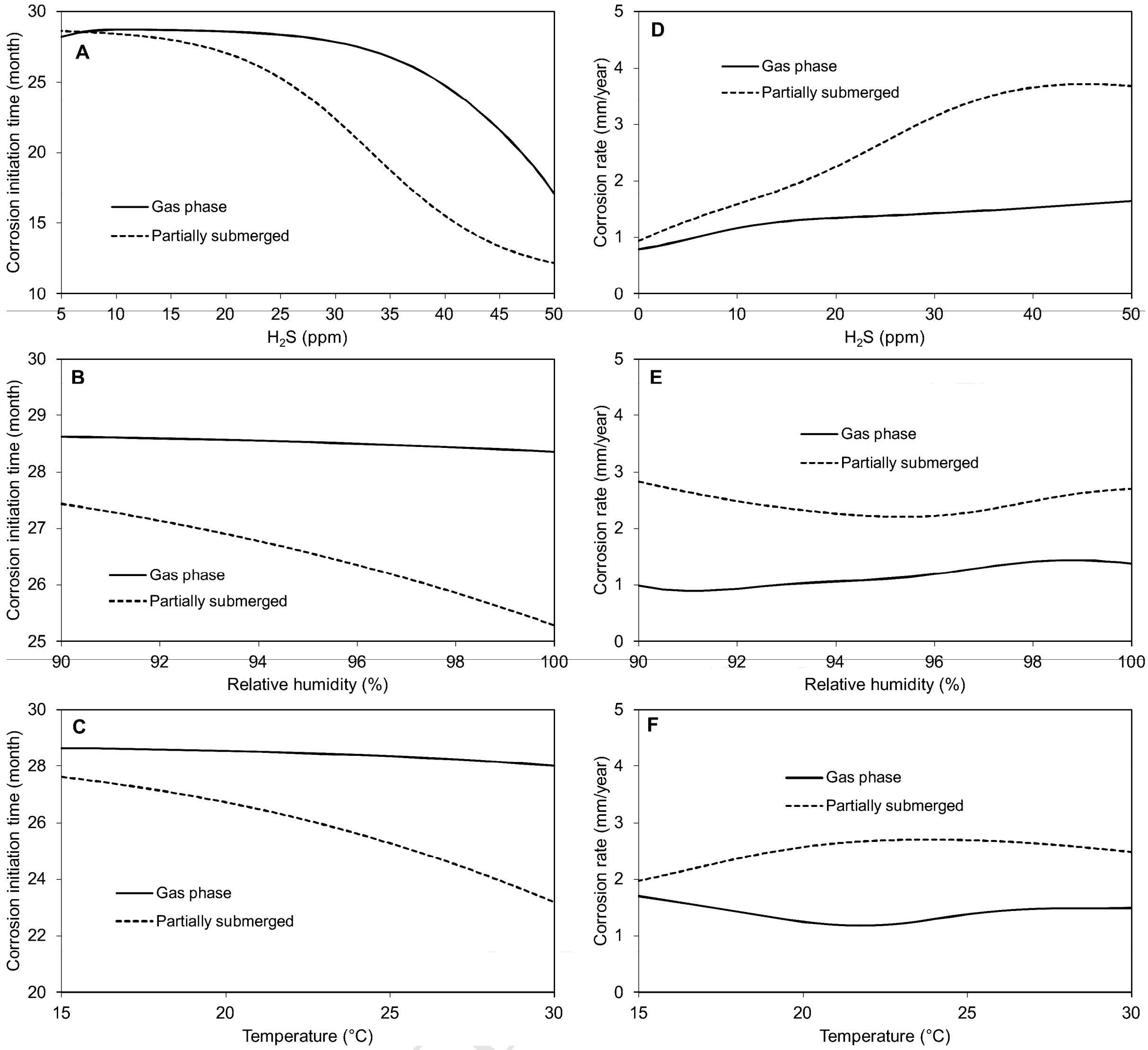

Figure 7. Sensitivity of corrosion initiation times (A, B and C) and corrosion rates (D, E and F) to H_2S concentration, RH and temperature for the ANN models described in sections 3.1 and 3.2.

Additionally, the sewer corrosion at the two different locations (gas phase (GP) and partially submerged (PS)) showed different levels of sensitivity to all sewer environmental factors. The corrosion initiation of GP sewer is more sensitive to the change of environmental factors while PS sewer is barely affected by RH and temperature. This reflects that submerged coupons were not so much affected by humidity levels because of their proximity to water. Also, the corrosion rates of PS sewer showed much higher sensitivity to H_2S than that of GP sewer. Possibly, this is resulting from PS sewer having higher maximum corrosion rates that are influenced by the availability of nutrients and water or the high wash-off of corrosion products due to the shear force of wastewater.

The results of the sensitivity analysis reveal details of the underlying mechanisms of sewer corrosion. For sewer corrosion, primarily caused by acid production through sulfide oxidation, the reaction kinetics are usually expressed as an exponential function ($y = k \cdot x^n$), where the exponent value relates to the long-term corrosion. When the corrosion is controlled by H_2S diffusion through the corrosion product, the value of the exponent is 0.5. From the ANN predictions, the values of n are 0.20 ± 0.01 and 0.53 ± 0.04 for GP and PS sewers respectively (Figure 6D). This suggests that the corrosion products on PS sewer act as a form of diffusion barrier. The extent of corrosion on GP sewer is lower and thus the diffusion limitation is less obvious.

There are still considerable unexplained variances in the neural network predictions. Such unexplained variances are mainly attributable to two reasons: ignorance of other important affecting variables and inherent scattering in the data. There are some potential affecting variables that have not been considered in the ANN analysis. For example, our recent study indicates that, in comparison to even concentrations of gaseous H_2S, daily fluctuating levels that occur in real sewers can affect the H_2S oxidation pathway and the total amount of H_2S uptake by the sewer concrete (Sun et al., 2015). Another possible factor not considered is the periodic inoculation of the concrete surface that occurs in real sewers by sewage due to changing water levels (e.g. flooding) and splashing. This could accelerate the initiation of corrosion and corrosion rate on frequently wetted concrete. Additionally, different sewer pipes are made of different cements and aggregates with different water to cement ratios.

Therefore, the concrete properties and other variables could be included for expansion of the ANN model.

To obtain reliable predictions, the use of the ANN model should be limited to the range of the factors used to train the model, i.e. H_2S gaseous concentration between 0 and 50 ppm, RH between 90% and 100% and temperature between 17 °C and 30 °C. Nevertheless, the ANN model has a strong capability of scatter-tolerance and it is expected that the prediction accuracy of the model will increase with the consideration of more affecting factors and the inclusion of more data in the model training process.

4 Conclusions

This study developed a predicting tool for the estimation of the service life of concrete sewers based on the modelling of sewer corrosion through an artificial neural network. 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. This has led to the following key findings:

- Artificial neural network performs well in predicting the time for corrosion to initiate on sewers and the corrosion rate based on four parameters related to the sewer environmental conditions.
- The ANN model trained with laboratory data provided better estimations to field measurements in real sewers than the multiple regression model. Although, the multiple regression model can be used as a simple and quick tool to estimate corrosion rate.

- The ANN model can be used to understand the corrosion mechanisms and be further improved by including more affecting factors or training with corrosion data under broader conditions including H_2S concentration, humidity and temperature.

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Figure 4. Validation of the ANN and multiple regression (MR) model using corrosion initiation time observed in real sewers.

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Figure 6. Validation of the ANN and multiple regression (MR) models using corrosion rates observed in real sewers. The ANN predictions were improved by including corrosion rates observed in real sewers in the model training process.

Figure 7. Sensitivity of corrosion initiation times (A, B and C) and corrosion rates (D, E and F) to H_2S concentration, RH and temperature for the ANN models described in sections 3.1 and 3.2.

Highlights

- Service life of corrosion impacted sewer depends on the initiation time and corrosion rate
- Artificial neural network was trained with 4.5 years of corrosion data obtained in lab
- Trained ANN model predicts reasonably the corrosion observed in real sewers
- ANN performs better than the multiple regression model in predicting sewer corrosion
- ANN model can be improved with more training data or the inclusion of more factors