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AN EVOLUTIONARY POLYNOMIAL REGRESSION (EPR) MODEL FOR PREDICTION OF H2S INDUCED CORROSION IN CONCRETE SEWER PIPES

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The sulphuric acid is a known growing threat to concrete sewer pipes. Acid production is dictated by rapid urbanisation, increased use of hot water and discharge of toxic metals and sulphate containing detergents into the wastewater. Concrete sewer pipe corrosion due to sulphuric attack is known to be the main contributory factor of pipe degradation. Very little tools are available to accurately predict the corrosion rate and most importantly the remaining safe life of the asset. This paper proposes a new robust model to predict the sewer pipe corrosion rate due to sulphuric acid. The model makes use of a powerful Evolutionary Polynomial Regression method that provides a new methodology of hybrid data-mining. The results obtained by the model which was validated in the field indicates that the proposed hybrid methodology can accurately predict the corrosion rate in concrete sewer pipe's given that the pipe installation conditions as well as in-pipe sewage conditions are known.

Key words: EPR, corrosion, sewer pipes, sulphuric acid.

INTRODUCTION

All over the world the costs involved in dealing with sewer pipe corrosion are escalated to billions of dollars per year [1], as a consequence of corrosion process, pipes collapse and may cause surface flooding.

In USA there are around 550,000km of concrete pipes. Annual rehabilitation costs of concrete sewers on its own for Los Angeles county rounded to €400 million [2]. Where it was estimated that in total in USA an annual cost of water and wastewater asset concrete corrosion is costing $36 billion [3] and given the aging infrastructure, more intense use and higher rate of degradation the renovation cost are expected to increase [2, 4]. In city of Sarnia, Canada, 440m of sewer main on Calbrone Street had to be replaced after collapse due to corrosive deterioration which resulted in a cost of $350,000 [5].

In Australia and New Zealand since 1910 the majority of pipes are chosen to be of steel-reinforced concrete material, and currently there are around 300,000km of concrete pipes installed between both countries [6]. Figures suggest that Australia has 110,000km of concrete sewers [7] and on average the pipe corrode at a rate of 1-3mm a year [6]. In Sydney area alone there are nearly 900km of concrete sewer pipes, with annual expense of AUS $40 million on rehabilitation program [8].

In continental Europe the sewer pipes of 250-800mm in diameter are dominantly classified as concrete pipes that were primary installed in 1930-1980th. As example, in the city of Hague, Netherlands, 95% of sewer pipes are of concrete material [9]. In Germany the costs of concrete sewer rehabilitation due to corrosion were estimated to be €100 million [5, 10]. Overall, continental European cities are calculated to spend more than €5 billion on sewer rehabilitation each year [11].

UK holds the most aged sewer system network in the world with majority of pipes being installed in 19th century. Total length of sewer pipes in the UK reaches 392,599km, from which 70,667km are concrete pipes [12]. In the last operational year 2012/2013 alone in the UK concrete sewer pipes experienced 11,165 collapses, most caused by pipe deterioration due to biochemical induced corrosion, and 8,864 main bursts all leading to 1800 incidents of internal property flooding of which 209 are classified as severe [12, 13]. Overall, these incidents are costing £84.8 million annually to the water authorities, companies and consumers in the UK [14]. To overcome this problem water companies are renovating and replacing approximately 550km of sewers a year which accounts only for 0.14% of overall sewer length in the UK [13,14] and is insufficient to fight against aging pipe network.

The build-up of sulphide is considered to be one of the most critical problems in aged concrete wastewater pipes, where sulphide production and emission is the dominating cause of pipe crown and walls corrosion. Furthermore, extended facts suggest that the primary reason for concrete pipe failure is the deterioration caused by the corrosion process [15-18]. Due to a complex interaction between factors resulting in pipe wall corrosion, the rate at which a pipe corrodes is unique. To support this there are known a number of cases which show that the pipes may collapse in 3-20 years' time when designed to last 50-100 years [15, 19]. In general the sewer pipe wall corrosion rate is governed by the rate at which the sulphuric acid is generated as well as the chemical and structural properties of the concrete material. Due to the chemical processes which take place in the gas phase and effluent interaction the sulphides are formed which facilitate the production of sulphuric acid. The last acts as a conductor between hydration product, present in concrete pipe wall, transformation into calcium sulphate or gypsum [20]. The chemical mutation which is involved in sulphide build-up is well understood, where the microbiologically induced corrosion or sulphide corrosion has two stages: In the first stage the sulphate contained in wastewater is converted into sulphide in solid and gaseous form as hydrogen sulphide. In the second stage the hydrogen sulphide is converted into sulphuric acid, which is the main component facilitating the pipe wall corrosion process.

Accurate estimations of sulphide build-up as well as models predicting the remaining safe life of the buried concrete sewer pipes have been studied before. Among those there are techniques which are based on deterministic models, statistical models, probabilistic models, Artificial Neural Networks (ANN) and Fuzzy logic, however none of those have considered in depth a full range of parameters influencing sewer failure as well as used extended real life sewer data to validate the model [21].

Current paper will use Evolutionary Polynomial Regression (EPR) to estimate the remaining safe life of a given section of a sewer pipe where the model was trained and further calibrated purely based on extended data measured in the field as well as historical data available for the selected sewers.

FIELD EXPERIMENTS AND DATA

Extended field data was collected in Neulengbach, Vienna Region, Austria in partnership with University of Natural Resources and Life Sciences (BOCU) and water asset management company AWV Anzbach Laabental.

A total number of 142 concrete pipe sections, most with corrosion problem were selected. Pipes were chosen to represent a range of internal diameters (D) of 300mm, 400mm, 500mm, 600mm, 800mm and 1200mm, where the largest population studied were 300mm pipes, totaling to 105 sections. Predominantly the selected pipe sections were installed in 1980's and on the time of survey had an age of 21-29 years (y). Table 1 shows measured parameters minimum, maximum and mean values, where columns left to right show pipe diameter, slope, water depth, flow width, flow velocity, effluent temperature, temperature of air above the effluent, estimated concentration of dissolved sulphite and value relative to pH. Parameters C_1 and C_2 will be explain in the next section. Flow depth and width was calculated as annual averaged based on visual data available in periods from 2006-2012. Temperatures were measured in 2014 and in combination with historical meteorological data [22] annual average values were estimated.

Table 1. Statistical values of measured pipe and effluent parameters

Value	**D [mm]**	**s [-]**	**h [mm]**	**b [mm]**	**u [m/s]**	**T_s [C]**	**T_a [C]**	**DS [-]**	**j [-]**	**C_1 [mm/y]**	**C_2 [mm/y]**
Min	300	0.0003	4.50	72.93	0.36	11.82	10.00	0.00	0.03	0.03	0.02
Max	1200	0.09	200.00	731.17	9.12	13.10	14.40	5.39	0.20	1.01	1.04
Mean	385.21	0.02	45.18	222.50	2.95	11.82	12.50	0.85	0.07	0.26	0.23

Moreover, the chemical properties of the effluent as concentration of biological oxygen demand [BOD_5] and pH were measured in 2014, these ranged between 140-520ml/l and 7.6-8.53, respectively. The [BOD_5] was used to calculate the total sulphite build-up value d[S]/dt as described in [15], see Eq. (1) where (r) is pipe internal radius. Further these values were used to estimate the concentration of dissolved sulphite [DS] as described in [23], see Eq. (2). Values of pH were further used to obtain relative (j) values introduced by [19], see Eq. (3) which is only valid for pH values in range of 7-8.6.

$$\frac{d[S]}{dt} = 10^{-3}[BOD_5](1.07)^{(T_s-20)} r^{-1}(1+0.37D) \tag{1}$$

$$[DS] = \left(0.8\frac{d[S]}{dt}\right) - 0.2 \tag{2}$$

$$j = 0.1965(pH)^2 - 3.3568(pH) + 14.37 \tag{3}$$

MODEL PRINCIPLES

The evolutionary polynomial regression (EPR) method is a fairly novel technique adopted in artificial intelligence (AI) modelling. This method is a data-driven technique which has an ability to process and learn large number of data which do not exhibit linear relation and provide a desirable solution based on input parameters. EPR makes use of a combination of genetic algorithm (GA) and least square (LS) in order to generate a pseudo-polynomial regression model suitable to supplied library of data. A general EPR expression can be presented in the following form [24]:

$$y = \sum_{i=1}^{n} F\left(\mathbf{X}, f\left(\mathbf{X}\right), a_i\right) + a_0 \tag{4}$$

where y is the desired system output, i is a sequential number, n is the total number of terms in the expression which excludes the bias term a_0, F is a function constructed by the process, a_i is a constant, $\mathbf{X}$ is the matrix of input variables and f is the function defined by the user. The core functional structure in Eq. (4), which is represented by $F(\mathbf{X}, f(\mathbf{X}), a_i)$, is constructed by EPR from basic functions using genetic algorithm (GA), which selects the useful input vectors from $\mathbf{X}$ to be combined together [15]. The user defines the elements of the structure F based on engineering problem and physical 26understanding of the process. The evolutionary process is responsible for selecting and combining the feasible elements of the structure, whereas the least square method estimates the a_i parameters [15].

EPR method modelling is commenced by evolving equations, where the number of contributing parameters that represent the studied phenomenon is increased together with amplified evolutions. The accuracy of the developed model is measured by the coefficient of determination (CD) at each evolutionary stage:

$$CD = 1 - \frac{\sum_N \left(Y_a - Y_p\right)^2}{\sum_N \left(Y_a - \frac{1}{N}\sum_N Y_a\right)^2} \tag{5}$$

where N is the number of data points on which the CD is computed, Y_a is the actual input values, Y_p is the EPR prediction value.

The EPR technique makes use of a range of objective functions which help to optimize the outcome based on physical sense. With the development of EPR technique the output objectives previously only based on the accuracy of fitted data expanded to multi-objective genetic algorithm (MOGA). The multi-objective EPR focuses on optimising two or more objective functions, where one would control the model fit, and one or more would control the model complexity and physical logic. This approach enables to receive the best possible solution which allows the user to select the combination of model complexity and best fit [24, 25]. The study presented in this paper will use the multi-objective EPR technique [15].

SIMULATION AND RESULTS

The data for 142 pipe sections was used in EPR model simulation. Before the training process started the available data was split into two groups, independent training and validation. Training data was chosen to represent the same statistical population as those for validation. This was ensured by including statistical analysis and comparison of minimum, maximum, mean and standard deviation values for all contributing parameters relevant to each pipe section. Additionally, to avoid extrapolation, it was ensured that the statistical parameters of the validation data fell between the minimum and maximum values of the training data. From the above, the data with the closest values of mean and standard deviation from training and validation groups were used to carry out EPR model development. This process ensures adaptive learning of the EPR model and construction of the optimized output model.

When the subsequent assembly of EPR model begins a number of settings (i.g. function type, number of terms, exponent range, etc.) can be adjusted, further step-by-step the EPR model involves outlined parameters and includes them in model build-up. Each developed model is trained and validated using set data pools, where at each stage the model accuracy is measured by the use of CD, see Eq. 5.

Carrying out the steps detailed above for several EPR runs and trying out different combinations of input and model parameters, two robust models, see Eq.(6) and (7), have been developed to predict the corrosion rate C_1 and C_2 (mm/y) of a concrete pipe:

$$C_1 = 39.6\frac{(hs)^{0.05}}{u^{0.1}} - 10.96\frac{D^{0.1}}{b^{0.35}T_s^{0.05}} - 31.46 \tag{6}$$

$$\begin{aligned} C_2 = {} & \frac{-0.016u^{0.4}h^{0.5}}{D^{0.25}(bT_a[DS])^{0.05}}\left(\frac{T_s j}{s}\right)^{0.15} - 4.471\left(\frac{1}{D}\right)^{0.15}\left(\frac{hu}{b}\right)^{0.05} + 65.47\left(\frac{1}{D}\right)^{0.05} \\ & -35.62\left(\frac{1}{b}\right)^{0.05} + 29.03\left(\frac{1}{u}\right)^{0.1}(Dhs)^{0.05} - 0.135\frac{D^{0.15}}{s^{0.1}}\left(\frac{bu}{T_s}\right) - 52.67 \end{aligned} \tag{7}$$

where in both equations h is the flow depth, s is the pipe slope, u is the flow velocity, D is pipe internal diameter, b is flow width, T_s is effluent temperature, T_a is the temperature of air above the effluent, [DS] is the concentration of dissolved sulphite in the effluent calculated by Eq. (1) & (2) and j is the value relevant to effluent pH calculated by Eq. (3). Both of these models were selected based on physical sense they exhibit and scientific findings which explain the process of corrosion build-up in pipes.

Model predicting corrosion rate in millimeters per year (see Table 1) which is shown in Eq. (6) has demonstrated a coefficient of determination of 95% and is quite simple to be used by an operator. C_1 model has three terms and mainly concentrates on pipe geometry, flow velocity and basic geometry in cross-section as well as effluent temperature. A similar model without a temperature factor was tested and it was found that a CD of 48% could only be achieved. This indicates the high importance of the temperature factor to be included in the analysis and the influence of the temperature on corrosion rate and further prediction.

Model predicting the corrosion rate (see Table 1) shown in Eq. (7) is more complex to that shown in Eq. (6). C_2 model has seven terms and several repetitions of factors which are related to pipe geometry and flow, additionally factors as T_a, [DS] and j appeared in this model (compared to C_1 model) and the coefficient of determination of 99% is achieved. This semi-empirical model suggests the importance of effluent pH and dissolved sulphate values as well as the above effluent temperature which all affect the creation of H2S gas that directly influence the corrosion process if the pipe wall.

The discrepancy between the prediction models in Eq. (6) & (7) is small in terms of predicting the yearly corrosion rate in (mm) and the total remaining safe life of a given pipe section. Figure 1 demonstrates the corrosion rate of 114 pipe sections, which were classified to suffer from corrosion (C<1mm on 2006-2012 survey), predicted by the both models C_1 and C_2. The mean value of corrosion rate of 0.26mm/y and 0.27mm/y and standard deviation of

0.15mm/y and 0.15mm/y was predicted by both models respectively. In 78% of cases C_2 predicts the higher rate of corrosion than the one shown by C_1 model and in only in 5% of the cases model C_1 (sections 52, 53) predicts considerably higher corrosion rate than that in C_2.

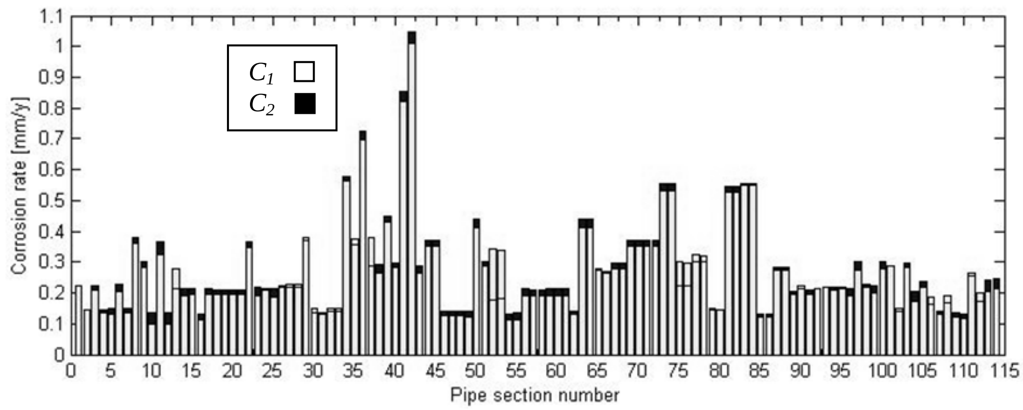

Figure 1. Pipe section corrosion rate predicted by models C_1 and C_2.

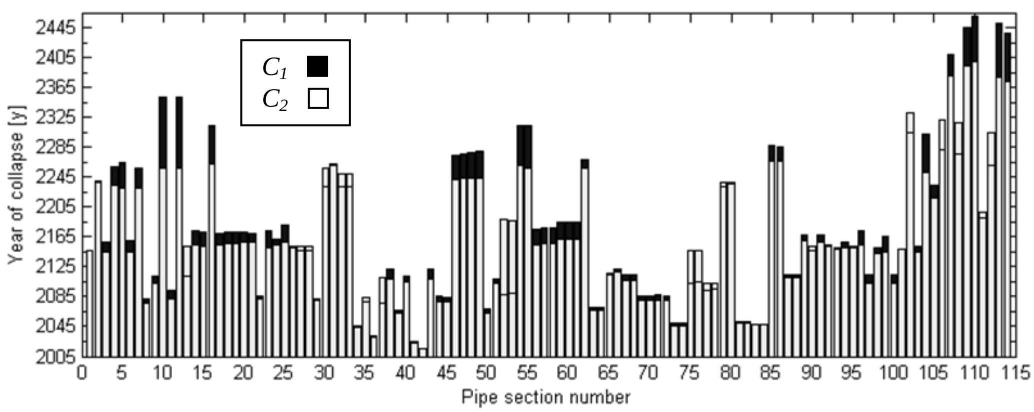

Figure 2. Pipe section year of collapse as predicted by models C_1 and C_2.

Figure 2 demonstrates the predicted year of collapse for each pipe section based on the knowledge of corrosion rate predicted by models C_1 and C_2 and the knowledge of pipe wall thickness. It was estimated that the pipe failure occurs when 75% of pipe wall thickness is corroded as well as it was assumed that corrosion rate remains constant with time. On average models C_1 and C_2 predict that the pipes will collapse in year 2217 and 2210 with standard deviation of 117 and 103 years, respectively. Interestingly that the pipe sections No. 41 and 42 located in sequence were predicted to collapse in year 2023 and 2015 by model C_2. The initial recorded survey was carried out in 2006, which showed corrosion level of 24mm and 30mm in these pipe sections respectively. On secondary survey, which took place in autumn 2013, most of the pipe wall crone was gone and the decision was made by the managing company to replace the pipe section shortly before any severe consequences were faced.

A sensitivity analysis was carried out for both of the models, as described in [15], to identify the parameters which by most influence the equation. Table 2 summarises the results for both models, where parameter sensitivity in the equation is expressed in percentage.

Table 2. Sensitivity analysis of parameters involved in models C_1 and C_2, shown in %

Model	D	s	h	b	u	T_s	T_a	DS	j
C_1	10.43	22.61	25.22	17.39	20.87	3.48	-	-	-
C_2	12.48	20.80	22.19	19.42	20.11	1.39	0.35	1.18	2.08

In models C_1 and C_2 the corrosion rate was found to decrease with increasing values of *D*, *u* and *j*, where opposite relation was observed for other values. In model C_1 all parameter weights were rank as *h*, *s*, *u*, *b*, *D*, *Ts*, with first having the most influence. This was confirmed in model C_2, where the parameters were ranked as *h*, *s*, *u*, *b*, *D*, *j*, *Ts*, *[DS]*, *Ta*. Surprisingly, the last four parameters had very little effect on the equations, however they do improve the general fit of the model. It is believed that the sensitivity of these parameters in the model are minimal due to the very specific, and in temperature perspective - small, range of values and thought that their weight will significantly increase when the extended range of these values will be considered.

CONCLUSIONS

This paper presents the Evolutionary Polynomial Regression (EPR) method which was used to develop a model capable of predicting the corrosion rate in concrete sewers and as a consequence estimate the remaining safe life of the pipe section. The model was created based purely on field data of live sewers. The data was collected in 142 pipe sections located in Neulengbach, Vienna Region, Austria. Primarily the pipes were of 300mm in diameter, however few sections of 400-1200mm were also studied, all within 21-29y group. Pipe geometrical parameters and effluent characteristics were collected between 2006-2014 and hence the average annual data was used in EPR. As a result of simulation two models were created, where factors such as *h*, *s*, *u*, *b*, *D*, *j*, *Ts*, *[DS]*, *Ta*, were considered. First model had 3 terms and expressed a coefficient of determination of 95%, whereas the second model had 7 terms and suggested an accuracy of 99%. Both models are true for the range of pipe sizes and conditions considered in the model, whereas to generalise these models a calibration on larger classes of pipes with extended variety of physical and chemical conditions as well as possibly mechanical loading from soil and traffic are required.

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