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Abstract:

Concrete corrosion due to sulphuric acid attack is known to be one of the main contributory factors for degradation of concrete sewer pipes. This paper proposes to use a novel data mining technique, i.e. evolutionary polynomial regression (EPR), to predict (i) the mass loss and (ii) the compressive strength of concrete subject to sulphuric acid attack. A comprehensive dataset from literature is collected to train and develop the EPR models. The results show that the EPR models can successfully predict the mass loss and compressive strength of concrete specimens exposed to sulphuric acid. Parametric studies of the models show that the proposed models are capable of representing the degree to which individual contributing parameters can affect the mass loss and compressive strength of concrete. In addition, based on the developed EPR models and using optimisation techniques, the optimum concrete mixture to provide maximum resistance against sulphuric acid attack is obtained.

Keywords: Evolutionary computing; genetic algorithm; evolutionary polynomial regression; optimisation; hybrid techniques; data mining; sulphuric acid attack; degradation; corrosion; sewer pipes

1. Introduction

Sewer systems are essential infrastructures that play a pivotal role in economy, prosperity, social well-being, quality of life and especially the health of a country. The nature of the wastewater and the propensity for anaerobic conditions in the buried pipes lead to complex chemical and biochemical transformations in the pipes, resulting in the inevitable deterioration of pipe materials due to a variety of mechanisms such as hydrogen sulphide induced corrosion of concrete. The sewer networks have had to expand as a result of population growth and thus the extended hydraulic retention time of wastewater in the sewer pipes tends to create a suitable environment for sulphide production, leading to the corrosion of pipes. In addition the widely projected climate change induced temperature rise will further accelerate corrosion. This pipe corrosion results in the reduction of wall thickness, leading to the collapse of the pipes and possibly the whole system, unless proactive intervention is carried out in a timely manner, based on an accurate prediction of their remaining safe life. The consequences of the collapses of sewers are socially, economically and environmentally devastating, causing enormous disruption of daily life, massive costs, and widespread pollution and so on.

Concrete corrosion due to sulphuric acid attack is known to be one of the main contributory factors for degradation of concrete sewer pipes. Sulphate, which exists in wastewater, is reduced to sulphide by anaerobic bacteria. These bacteria are present in a thin slime layer on the submerged surface of the sewer pipe and the production of sulphide occurs in this slime layer. The generated sulphide escapes to the exposed sewer atmosphere where it is transformed to sulphuric acid by aerobic bacteria. The acid reacts with calcium hydroxide in the cementitious sewer pipe which forms gypsum and causes corrosion [1-3].

Pomeroy 1976 [2] proposed a model to predict the corrosion rate in cementitious sewer pipes.

$$c = 11.5\frac{k\emptyset_{sw}}{A} \tag{1}$$

In this equation, c is the average rate of corrosion of the material (mm/yr), k is a factor representing the acid formation based on climate condition, $\emptyset_{sw}$ is the average flux of sulphide to the pipe wall ($g/m^2 - hr$) and A is the alkalinity of the pipe material.

Equation 1 shows that among various pipe material properties, only alkalinity (A) influences the corrosion of concrete sewer pipes. Many researchers have investigated the effect of acid attack on different mixtures and admixtures of concrete. Attiogbe and Rizkalla [4] evaluated the response of four different concrete mixtures including two different cement types (ASTM Type I and ASTM Type V) to accelerated acid attack. The concrete samples were immersed in sulphuric acid solutions with a pH of 1.0. This concentration of sulphuric acid was selected since it was a representative of what is expected in sewer pipes in the process of deterioration. After 70 days of immersion, the results of the experiment showed that the weight loss of concrete samples with cement Type V is slightly more than those samples created with cement Type I. It was concluded that in the long term, the sulphate resistant cement does not contribute to an improved resistance of concrete compared to ordinary Portland cement when they are subject to sulphuric acid attack. Ehrich et al. [5] carried out biogenic and chemical sulphuric acid tests to monitor the corrosion of different cement mortars. They used ordinary and sulphate resistant Portland cement as well as calcium aluminate cement to produce different mortars. The biogenic tests were carried out using a simulation chamber where the temperature, humidity and amount of sulphide were monitored and controlled. For the chemical test, the mortar samples were immersed in PVC containers filled with sulphuric acid. The results of both chemical and biogenic tests showed that calcium aluminate cement mortars had greater resistance against both types of acid attacks. Monteny et al. [6] simulated chemical and biogenic sulphuric acid corrosion of different concrete compositions including ordinary and polymer cement concrete. For the biogenic tests, they put small concrete samples in a microbiological suspension containing bacteria, sulphur and nutrients which generated sulphuric acid in a biogenic manner. The chemical tests were performed using a rotating apparatus. Concrete samples were set up on an axis which was rotating in such a way that the concrete samples were only partially immersed in a solution of sulphuric acid with a pH of around 1.0. The results of both tests revealed that concrete mixtures with styrene-acrylic ester polymer showed a higher resistance compared to the concrete with high sulphate resistance cement. On the other hand the concrete mixtures with acrylic polymer and styrene butadiene polymer showed a lower strength than the high sulphate resistance concrete. De Belie et al. [7] presented the results of biogenic and chemical sulphuric acid tests carried out on different types of commercially produced concrete sewer pipes. They performed both types of tests on different mixtures of concrete including different aggregate and cement types. The results of both chemical and biogenic tests showed that the aggregate type had the largest effect on degradation of concrete samples. In addition, based on the results obtained from their studies, they proposed an equation to predict the degradation depth taking into account both alkalinity and water absorption of concrete (Equation 2).

$$C = \frac{c_1}{A} + c_2 W \tag{2}$$

where C is degradation depth after four cycles of the microbiological test (mm), A is alkalinity, W is water absorption (%) and c_1 and c_2 are the coefficients of the equation. Chang et al. [8] investigated the use of different aggregates and cements to improve the resistance of concrete subject to sulphuric acid attack. The concrete samples were produced with limestone, and siliceous aggregate, and Portland, binary and ternary cements. The water/cement ratio was kept constant (i.e. W/C=0.4) for all the samples. The concrete specimens were immersed into a sulphuric acid solution with a pH between 1.27 and 1.35. The changes in weight and compression strength of samples were examined at different ages up to 168 days. It was shown that the use of limestone aggregates and ternary cement containing silica fume and fly ash will help to reduce the weight loss and reduction in compressive strength of concrete under sulphuric acid attack. Hewayde et al. [9] carried out an investigation on 78 different concrete mixtures including different cement types, different water/cement ratios and various admixtures subject to sulphuric acid attack. The concrete samples were immersed in sulphuric acid solutions with pH levels of 0.3, 0.6, and 1.0. The authors stated that the solution with a pH of 0.6 represents conditions with a high count of anaerobic bacteria that exist in the submerged surface of the sewer pipes, while the solution with a pH of 0.3 represents a supercritical condition that may occur in industrial sewer systems subject to high temperature and humidity. The experiment consisted of determining the compressive strength of samples at different ages and measuring the changes in weight at different pH values. Using the data collected from the tests, they developed two artificial neural network (ANN) models to predict the mass loss and compressive strength of concrete. They showed that the developed ANN models are capable of predicting both compressive strength and mass loss of concrete samples under exposure to sulphuric acid, providing the required parameters (i.e. the concrete contents) have been inputted. The studies presented above and many more in literature show that the constituents of concrete mix including admixtures play an important role in the alkalinity of concrete and consequently its vulnerability to sulphuric acid induced corrosion. However, insufficient work has been carried out in relation to the modelling and prediction of deterioration and compressive strength of concretes with various mixtures subject to sulphuric acid. No doubt the development of such model(s) would help industry to evaluate and possibly improve the concrete mix design of their sewer pipes. In addition if the concrete content of existing pipes is known, water companies can carry out proactive intervention, based on the accurate predictions provided by such models.

The rapid development in computational software and hardware in recent decades has introduced several soft computing and data-driven approaches to modelling engineering problems. Although there are various data-driven techniques based on artificial intelligence, artificial neural network (ANN) and genetic programming (GP) are among the best known techniques that have been used to model civil and mechanical engineering problems. ANN uses models composed of many processing elements (neurons) connected by links of variable weights (parameters) to form black box representations of systems. ANNs are capable of dealing with a large amount of data and can learn complex model functions from examples, by training sets of input and output data. ANNs have the ability to model complex, nonlinear processes without having to assume the form of the relationship between input and output variables [10, 11]. However, ANN has shown to possess some drawbacks. A major disadvantage of ANN is the large complexity of the network structure; it represents the knowledge in terms of a weight matrix and biases which are not accessible to the user. ANN models, as a black box class of models, gives no information on how the input parameters affect the output(s). In addition, parameter estimation and over-fitting are other disadvantages of models constructed by ANN [12, 13]. Genetic programming (GP) is another modelling approach that has been used to model engineering phenomena. GP is an evolutionary computing method that generates transparent and structured mathematical expressions to represent the system being studied. The most common type of GP method is symbolic regression, which was proposed by Koza [14]. This technique creates mathematical expressions to fit a set of data points using the evolutionary process of genetic programming.

The genetic programming procedure mimics natural selection as the 'fitness' of the solutions in the population improves through successive generations. However, GP also has some limitations. It is proven that GP is not very powerful in finding constants and, more importantly, that it tends to produce functions that grow in length over time [12].

In this paper, using a dataset collected from literature and a novel hybrid data-driven technique that overcomes the shortcomings of ANN and GP, models are developed to predict the degradation and compressive strength of concrete subject to sulphuric acid attack. This new data mining technique, called evolutionary polynomial regression (EPR), provides a structured, transparent and concise model representing the behaviour of the system. A brief description of the EPR technique is provided in what follows. Then development of the models to predict the degradation and compressive strength of concrete subject to acid attack is presented. Using the developed models and optimisation techniques, the optimum contents of concrete mixtures to resist against acid attack is obtained.

2. Evolutionary Polynomial Regression

Evolutionary polynomial regression (EPR) is a new hybrid technique for creating true or pseudo-polynomial models from observed data by integrating the power of least square regression with the efficiency of genetic algorithm. A typical formulation of EPR can be expressed in the following equation [12]:

$$y = \sum_{j=1}^{m} F(\mathbf{X}, f(\mathbf{X}), a_j) + a_0 \tag{3}$$

In this equation, y is the estimated output of the system; a_j is a constant value; F is a function constructed by process; $\mathbf{X}$ is the matrix of input variables; f is a function defined by user; and

m is the number of terms of expression excluding the bias term a_0. The general functional structure represented by $F(\mathbf{X}, f(\mathbf{X}), a_j)$ is constructed from elementary functions by EPR using genetic algorithm (GA). The function of GA is to select the useful input vectors from **X** to be combined together. The building blocks (elements) of the structure of F are defined by the user based on understanding of the physical process. While the selection of feasible structures to be combined is done through an evolutionary process, the parameters a_j are estimated by the least square method.

The modelling process of EPR starts by evolving equations. As the number of evolutions increases, EPR gradually picks up the different contributing parameters to form equations representing the system being studied. Accuracy of the developed models is measured at each stage using the coefficient of determination (CoD):

$$\mathrm{CoD} = 1 - \frac{\sum_{\mathrm{N}}(\mathrm{Y_a} - \mathrm{Y_p})^2}{\sum_{\mathrm{N}}(\mathrm{Y_a} - \frac{1}{\mathrm{N}}\sum_{\mathrm{N}}\mathrm{Y_a})^2} \tag{4}$$

where Y_a is the actual input value; Y_p is the EPR predicted value and N is the number of data points on which the CoD is computed. If the model fitness is not acceptable or other termination criteria (e.g., maximum number of generation and maximum number of terms) are not satisfied, the current model should go through another evolution in order to obtain a new model [15].

In order to provide the best symbolic model(s) of the system being studied to the users, EPR is facilitated with different objective functions to optimise. The original EPR methodology used only one objective (i.e., the accuracy of data fitting) to explore the space of solutions while penalising complex model structures using some penalisation strategies [12]. However the single-objective EPR methodology showed some shortcomings, and therefore the multi-objective genetic algorithm (MOGA) strategy has been added to EPR [16]. The multi-objective EPR optimises two or three objective functions in which one of them will control the fitness of the models, while at least one objective function controls the complexity of the models. The multi-objective strategy returns a trade-off surface (or line) of complexity versus fitness which allows the user to achieve a lot of purposes of the modelling approach to the phenomenon studied [16]. In this study the multi-objective EPR is used to develop the EPR-based models. Further details of the EPR technique can be found in [12, 15-16].

The EPR technique has been successfully applied to modelling a wide range of complex engineering problems including modelling sewer failure [17], pipe break prediction [18], mechanical behaviour of rubber concrete [19], torsional strength of reinforced concrete beams [20] and many other applications in civil and mechanical engineering. EPR is proven to be capable of learning complex non-linear relationships from a set of data, and it has many desirable features for engineering applications.

3. Development of Models

3.1 Database

The database to train and develop EPR models is collected from a study by Hewayde [21]. Hewayde [21] carried out a set of experiments to evaluate the compressive strength and mass loss of different concrete mixtures under sulphuric acid attack. The experiment program involved the preparation of several concrete cylinders with different contents, and then immersing them in sulphuric acid solutions with different pH values. The compressive strength at age 7, 28 and 120 days, as well as the weight loss of concrete samples, were measured and recoded. Two different cements (ASTM Type I and ASTM Type V), siliceous fine and coarse aggregate and various admixtures including silica fume, metakaolin, geopolymer cement, organic corrosion inhibitor (OCI), Caltite, and Xypex were used to prepare concrete specimens. The effect of using ASTM Type V cement in the mixtures were presented in terms of percentage of slag since Type V cement is a blended cement made of 65% ordinary Portland cement and 35% finely ground granulated blast furnace slag. The concrete samples had different values of water/cement ratio and aggregate contents as well as various percentages of superplasticizer and admixtures which made a very suitable collection of data to train and develop EPR models. Further details of the experiments are described in [9, 21].

3.2 EPR procedure

Two separate models are developed to predict the mass loss and compressive strength. The input and output parameters of each model and their units are presented in Table 1.

Usually in data mining techniques based on artificial intelligence such as neural network, genetic programming and EPR, the data is divided into two independent training and validation sets. The construction of the model takes place by adaptive learning over the training set and the performance of the constructed model is then appraised using the validation set. In order to select the most robust representation of the whole data for training and validation sets, a statistical analysis was carried out on the input and output parameters of several randomly selected sets of data. The purpose of the analysis is to ensure that the statistical properties of the data in each of the subsets were as close to each other as possible. After the analysis, the most statistically consistent combination was used for construction and validation of the EPR models. In addition the statistical analysis will help to keep the validation data in the range of the maximum and minimum values of the training data as generally the EPR technique (like other data-mining techniques) is stronger in interpolation than extrapolation over the data. Maximum, minimum, average and standard deviations are the parameters used to perform the analysis.

Once the training and validation sets are chosen, the EPR process can start. To develop the EPR models, a number of settings can be adjusted to manage the constructed models in terms of the type of the functions, number of terms, range of exponents, etc. [15]. When the EPR starts, the modelling procedure commences by evolving equations. As the number of evolutions increases, EPR gradually learns and picks up the participating parameters in order to form equations. Each proposed model is trained using the training data and tested using the validation data. The level of accuracy at each stage is measured using the CoD (Equation 4). Several EPR runs were carried out and the analysis was repeated with various combinations and ranges of exponents, different functions and different numbers of terms in order to obtain the most suitable form for the model. As mentioned earlier the MOGA-EPR returns a trade-off curve of the model complexity versus accuracy which allows the user to select the most suitable model based on his judgement and knowledge of the problem. The results of the EPR were analysed based on the simplicity of the models and the CoD values of both training and testing datasets. After analysis of different alternative models the following expressions are found to be the most robust models for predicting mass loss (model I) and compressive strength (model II). Among the developed models provided by EPR the ones with the least number of terms that include all the parameters and have the highest possible CoD have been chosen.

$$ML = 1.5\times10^{-4}Sg^2 + 4.7\times10^{-7}WSF\sqrt{S} - 2.2\times10^{-6}W\sqrt{HCltS} + 1.6\times10^{-2}\sqrt{GSg} - 1.5\times10^{-7}HGeo\sqrt{GpHWSg} + 2.8\times10^{-6}X\sqrt{GSM} - 1.3\times10^{-6}GW\sqrt{pH} + 1.9\times10^{-8}G^2\sqrt{W} - 9.4\times10^{-11}G^2SgS - 3.2\times10^{-4}\sqrt{CS} + 5.6\times10^{-8}SpH\sqrt{CWGeo} - 7.2\times10^{-13}G^3pH^2 - 5.8\times10^{-6}pH^2HC\sqrt{SFW} - 5.2\times10^{-7}CW\sqrt{H} + 3.3\times10^{-5}C\sqrt{G} - 2.2\times10^{-15}H^3S^3C\sqrt{GXpH} - 1.2\times10^{-10}C^2\sqrt{GSOCI} \tag{5}$$

$$f_c = 3.6\sqrt{t} - 1.7Sg - 5.1\times10^{-7}W^3\sqrt{X} - 9.0\times10^{-10}t^3S\sqrt{W} + 2.1\times10^{-5}S^2\sqrt{GSg} - 2.3\times10^{-8}S^3\sqrt{GSg} - 2.8\times10^{-9}H^3Sg^2GW - 3.5\times10^{-12}S^2G^2\sqrt{HM} + 5.2\times10^{-11}G^3SF\sqrt{WX} + 1.2\times10^{-3}SH\sqrt{C} + 7.2\times10^{-11}Sg^3S\sqrt{CWH} + 4.5\times10^{-12}S^3W\sqrt{C} + 8.5\times10^{-12}S^2CWM + 5.0\times10^{-12}Sg^3C\sqrt{GSM} + 1.0\times10^{-12}H^3CGSWOCI\sqrt{tSg} + 1.6\times10^{-10}G^3COCI\sqrt{SFCltGeo} - 1.8\times10^{-12}W^3C^2HOCI\sqrt{Xt} + 4.0\times10^{-13}C^2S^2t\sqrt{X} \tag{6}$$

The symbols used in these equations are described in Table 1. The predictions provided by model I and model II for both training and validation data is illustrated in Figure 1 and Figure 2 respectively. The CoD values of model I and model II are presented in Table 2. From Figures 1 and 2 and Table 2 it is evident that the EPR models perform well and represent a very accurate prediction for unseen cases of data.

3.3 Parametric study

A parametric study was carried out for further examination of the prediction capabilities of the proposed EPR models. The parametric study will help to assess the extent to which the EPR models represent the physical relationships between different parameters and the effects of different input parameters on the model output. All the input parameters except the one being examined were set to their mean values and the model predictions for different values of the parameter being studied were investigated. Each parameter was varied within the range of its maximum and minimum values. Figure 3 shows the results of the parametric study conducted to investigate the effect of change in cement content and W/C ratio on model I.

The results are presented for three different pH values (i.e. 0.3, 0.6 and 1.0). The results show that the mass loss of concrete subject to sulphuric acid attack escalates by increasing cement content or reduction in W/C ratio. Both of these behaviours are consistent with previous studies [9]. These results show that as the cement content of concrete increases, the sulphuric acid will expand its reaction with the cement which leads to further corrosion of the concrete.

The sensitivity of the EPR model I to one of the admixtures (OCI) is presented in Figure 4. It is evident from this figure that as the amount of OCI increases the mass loss is reduced. This indicates that adding a limited amount of OCI as a partial replacement of cement will reduce the deterioration of concrete against sulphuric acid.

In Figure 5 changes of compressive strength (model II) with cement content is presented. As expected the compressive strength of concrete samples exposed to sulphuric acid will rise as the cement content increases. This figure also shows that the compressive strength predicted by model II will improve as the age of concrete increases.

The same procedure was also used to determine the ability of model II to capture the sensitivity of compressive strength to variations of the Metakaolin and silica fume; the results are presented in Figures 6 and 7 respectively. These predictions are in agreement with those reported in [21].

It can be seen from the figures above that both models I and II were successful in capturing the sensitivity of mass loss and compressive strength to changes of different concrete mixture and admixture contents.

3.4 Simplified Models

As shown in previous sections, Equations 5 and 6 are the general EPR models that include all the mixture and admixture parameters and can accurately predict the deterioration and compressive strength of concrete exposed to sulphuric acid. However it is also possible to use these models for the concretes that have been prepared with no admixtures or with only some of the admixtures. This can be done by evaluating Equations 5 and 6 when those admixture parameter(s) are equal to zero. The results of such evaluations lead to the generation of more concise and practical equations that include all the essential concrete mixtures. As an example, Equations 5 and 6 are evaluated here for the case when no admixture is used, pH value is equal to 0.6 and the age of concrete to examine compressive strength is 28 days. The results of this simplification are presented in Equations 7 and 8.

$$\begin{aligned} ML = &-9.8\times10^{-7}GW + 1.9\times10^{-8}G^2\sqrt{W} - 3.2\times10^{-4}\sqrt{CS} - 2.6\times10^{-13}G^3\sqrt{CW} \\ &- 5.2\times10^{-7}CW\sqrt{H} + 3.3\times10^{-5}C\sqrt{G} \end{aligned} \tag{7}$$

$$f_c = 4.5\times10^{-12}S^3W\sqrt{C} + 1.2\times10^{-3}SH\sqrt{C} - 2.0\times10^{-5}S\sqrt{W} + 19.0 \tag{8}$$

The accuracy and sensitivity of Equations 7 and 8 were tested and verified to ensure that they provide reliable results.

4. Optimum mixture of concrete subject to sulphuric acid attack

From the results of parametric study it is evident that concrete contents may have different effects on the mass loss and compressive strength of concrete. For example while increasing cement content will improve the compressive strength of concrete it can cause further corrosion due to the mass loss. Therefore it is important to find a concrete mixture that can minimise the deterioration or maximise the compressive strength, or both at the same time, when the concrete is exposed to sulphuric acid attack. In this section, using optimisation techniques and simplified models (Equations 7 and 8), two different optimum concrete mixtures are presented that can provide maximum strength and minimum mass respectively. In addition, using a multi objective optimisation technique, a set of concrete mixtures that provide maximum strength and minimum mass loss is presented. Although only main concrete contents (i.e. cement, gravel, sand, water and superplasticizer) are optimised here, the technique can be extended to find both the optimum mixtures and admixtures using Equations 5 and 6.

4.1 Finding minimum mass loss

Equation 7 was minimised using a nonlinear programming optimisation technique. Lower limits and upper limits of each variable in the equation were set based on the minimum and maximum values of those parameters in the dataset. A constraint was defined to ensure that the total volume of concrete is always equal to unit value during the optimisation process (Equation 9). In addition, to obtain a practical solution W/C ratio was limited to 0.5.

$$V_{Gravel} + V_{Sand} + V_{Cement} + V_{water} + V_{superplasticizer} = V_{concrete} = 1.0\ m^3 \qquad (9)$$

The results of this optimisation are presented in Table 3. The results show that the presented combinations of concrete mixture will lead to a minimum 10% mass loss.

4.2 Finding maximum compressive strength

A similar procedure to that presented to find minimum mass loss was carried out to maximise Equation 8 in order to find the optimum concrete mixture that results in maximum compressive strength. The results of the optimisation are presented in Table 4. Table 4 shows that the above combination of concrete content will provide compressive strength of 72 MPa. It can be seen that, while the amount of aggregates has not changed much, the water and cement content of the mixture with maximum compressive strength is significantly different from those with minimum mass loss. This indicates the important role of the W/C ratio in concrete subject to sulphuric acid attack. While it seems that a higher W/C ratio is suitable to minimise the mass loss, it may result in a reduction of compressive strength of the concrete prepared with ordinary Portland cement. This has also been reported by other researchers in previous studies [22].

4.3 Multi-objective optimisation

A multi-objective genetic algorithm (MOGA) is used here to obtain optimum solution(s) that provide the minimum mass loss and maximum compressive strength of concrete simultaneously. The MOGA returns a Pareto front curve which contains a set of solutions rather than a single solution and the user can select the most suitable results based on the requirement of its own project. The same upper and lower limits and constraints to those of single-objective optimisation were set to perform the MOGA. In addition, different values of water/cement constraint were imposed to investigate the effect of these values. The GA was run several times for each W/C ratio to ensure that the final results are consistent and similar to each other. Once the optimisation terminated one solution from the Pareto front curve was selected for each W/C ratio as the optimum solution. The results are shown in Figure 8 and Table 5. The results of multi-objective optimisation, presented in Figure 8, also confirm the importance of water-cement ratio in the mass loss of concrete. The concrete mixture corresponding to each point on this graph is presented in Table 5. Similar optimisations can be run to obtain the optimum amount of other admixtures in concrete.

5. Summary and Conclusions

Sulphuric acid attack is recognised as one of the main causes for concrete sewer pipe degradation. Degradation of sewer pipes results in a reduction of the pipe's wall thickness and the eventual breakdown of the system. The collapse of sewer systems can incur many financial and social problems.

In this paper a new approach is presented for the prediction of degradation and compressive strength of concretes subject to sulphuric acid attack. Using a fairly comprehensive dataset from several acid attack experiments on various concrete mixtures and admixtures and a hybrid data mining technique (EPR), two models were developed and validated to predict the mass loss percentage and compressive strength of concrete when it is exposed to sulphuric acid. EPR integrates numerical and symbolic regression to perform evolutionary polynomial regression. The strategy uses polynomial structures to take advantage of their favourable mathematical properties. The developed EPR models present a structured and transparent representation of the system, allowing a physical interpretation of the problem that gives the user an insight into the relationship between degradation and various contributing parameters. An interesting feature of EPR is the possibility of getting more than one model for complex phenomena. The best model is chosen on the basis of its performances on a test set of unseen data. For this purpose, the initial dataset is split into two subsets, (i) training and (ii) validation. The validation data set is not seen by EPR in the model construction phase and predictions provided by EPR models based on this data can be used as an unbiased performance indicator of generalisation capabilities of the proposed models. Another major advantage of the EPR approach is that, as more data becomes available, the quality of the prediction can be easily improved by retraining the EPR model using the new data.

A parametric study was conducted to evaluate the effect of the contributing parameters (i.e. concrete contents) on the predictions of the proposed EPR models. Combined effects of the parameters were also considered in the sensitivity analysis to investigate the interdependencies of parameters and their effect on the EPR predictions. The results show that the developed EPR models provide very accurate predictions for both mass loss and compressive strength of concrete and are easy to use from a practical viewpoint. Using the developed EPR models, two simplified models were obtained in which they only include the essential concrete contents (i.e. cement, gravel, sand, water and superplasticizer). The proposed EPR models were optimised in order to find the optimum concrete mixture that provides the maximum resistance against sulphuric acid attack. The results of the optimisation confirmed that, similar to compressive strength, degradation or mass loss is highly dependent on water-cement ratio.

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