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ABSTRACT

Millions of dollars are being spent worldwide on the repair and maintenance of sewer networks and wastewater treatment plants. The production and emission of hydrogen sulphide has been identified as a major cause of corrosion and odour problems in sewer networks. Accurate prediction of sulphide build-up in a sewer system helps engineers and asset managers to appropriately formulate strategies for optimal sewer management and reliability analysis. This paper presents a novel methodology to model and predict the sulphide build-up for steady state condition in filled sewer pipes. The proposed model is developed using a novel data-driven technique called evolutionary polynomial regression (EPR) and it involves the most effective parameters in the sulphide build-up problem. EPR is a hybrid technique, combining genetic algorithm (GA) and least square (LS). It is shown that the proposed model can provide a better prediction for the sulphide build-up compared with conventional models.

KEYWORDS

Hydrogen sulphide; Sewer pipe; Sulphide build-up; Evolutionary polynomial regression

1 Introduction

Sulphide build-up is one of the major problems occurring in wastewater systems. The production and emission of sulphide is the main cause of corrosion and noxious odours in sewer systems [1, 2]. It is known that the degradation of sewer systems can be primarily attributed to corrosion induced by biogenic sulphuric acid attack, which causes severe structural deterioration and ultimate structural collapse [3-7]. There are many cases in which sewer pipes designed to last 50 to 100 years have failed due to hydrogen sulphide (H_2S) corrosion after only 10 to 20 years of service life. Such problems are rarely brought to the attention of the public until a catastrophic failure occurs. Prediction of sulphide build-up in sewer systems would greatly benefit the development of appropriate strategies for controlling sulphide formation or H_2S emissions. Accurate prediction of sulphide formation during both the design phase and operation of sewers is important for planning engineering measures to mitigate the sulphide related problems.

Since 1959, several steady-state empirical equations for prediction of sulphide build-up have been developed [8-10]. Although these models have been used as the basis for many studies in recent decades, there have been debates about accuracy and consistency of the models [11, 12]. Holder [11] noted that neither Pomeroy [8] equation nor Thistlethwayte's [9] equation is adequate for sulphide build-up prediction. He stated that, together with the intrinsic capacity of the slimes to convert sulphate to sulphide, the effects caused by mass transfer resistances in both the slime phase and the liquid should be taken into consideration in the development of improved predictive equations. The model by Boon & Lister [10] also does not consider stream velocity, which has been criticised by other researchers [13]. Recent studies focus on the dynamic change occurring in sewer systems [12, 14-15]. In dynamic analysis, the concentration of sulphide is predicted as a function of location with temporal variations.

In the present study a novel approach called evolutionary polynomial regression (EPR) is used to develop a model to predict the sulphide generation in filled sewer pipes. EPR introduces a new unified, clear and physically plausible framework in which different aspects of a system can be directly captured from experimental data and represented in the form of mathematical expressions. The developed models are capable of satisfactorily explaining the physics of the problem. The proposed model in this paper will be compared with existing conventional models to prove accuracy and reliability.

2 Formation of sulphide in sewer systems

Most sulphide in sewers is formed by bacteria thriving in a matrix of filamentous microbes and gelatinous material coating the inner submerged walls of wastewater pipes that is often referred to as the slime layer. Oxygen cannot normally penetrate this layer, leading to the formation of an inert anaerobic zone next to the pipe wall [16]. Insufficient ventilation of sewer pipes leads to the accumulation of hydrogen sulphide in the atmosphere on the pipe walls. The bacteria producing sulphide are strict anaerobes and, consequently, live beneath the water surface [17]. The bacteria may also thrive in sludge and grit deposits found along the bottom of pipes. The formation of sulphide compounds depends on the presence of components in the sewer that contain sulphur. Sulphate, generally abundant in wastewater, is usually the common sulphur source, although other forms of sulphur, such as organic sulphur from animal wastes, can also be reduced to sulphide [18-21]. The dissolved organic material prevalent in the wastewater provides an ample food supply for the bacteria to flourish. The reduction of sulphate in the presence of waste organic matter in a wastewater collection system can be described as follows [22, 23]:

$$SO_4^{2-} + \text{organic matter} + H_2O \xrightarrow[\text{Bacteria}]{} 2HCO_3^- + H_2S \qquad (1)$$

If concentrations of sulphate and dissolved organic material in the wastewater are high and if these materials are able to penetrate the solids deposits, then large amounts of sulphides can be produced. Once sulphides are produced in the wastewater as a result of sulphate reduction, H_2S gas will be released into the atmosphere [22-25]. In pressure mains (i.e., filled pipes) where the detention times are longer than, say, 10 minutes, there can be considerable sulphide build-up [22]. When the pump begins to operate, the heavy sulphide concentration is discharged, usually into a gravity sewer, where serious corrosion can take place if acid susceptible materials are used for the pipeline. These sources of deterioration are often disregarded by engineers when designing pumping stations and pressure mains. In some cases, it is difficult or not cost effective to design a sewer pipeline system that will be free of sulphide problems. It is then useful to know what levels of sulphide can be expected. The major determining factors for sulphide build-up are as follows [26, 27]:

1. The most fundamental quantity appearing explicitly or implicitly in these equations is the sulphide flux from the slime layer into the stream, expressed as grams of sulphide per square metre-hour (g/m^2-hr). Therefore hydraulic radius (which is represented by $\frac{1}{4}D$ for a circular cross section pipe) affects the rate of sulphide build-up.

2. The rate changes with temperature. While the chemical reaction presented in Equation (1) is accelerated in higher temperatures, the rate of sulphide build-up increases with increase of temperature.

3. The concentrations of organic nutrients and of sulphate. The rate of sulphide build-up can be limited by a scarcity of either sulphate or organic matter. Since both are consumed in the biological reactions that produce sulphide, they are required in a certain ratio. If there

is an excess of organic nutrients, then the rate is limited by the amount of sulphate and if there is an excess of sulphate it is limited by the amount of organic nutrients. The organic nutrients for sulphide generation are proportional to the chemical oxygen demand (COD).

4. (a) The stream velocity. At low velocity, solids may settle and move slowly and intermittently along the bottom. The loosely deposited solids quickly become depleted of oxygen, and sulphide generation proceeds until the depletion of sulphate or organic nutrients. Higher velocities increase oxygen absorption into the stream, increase the rate of oxygen transfer to the slime layer, and shorten the time that the sewage spends in transit, all of which lead to lower sulphide concentrations.

   (b) On the other hand, at low velocities, and especially if the sewage is intermittently stationary, nutrients may become depleted in the water adjacent to the slime layer, thus retarding sulphide generation. An increase of velocity in a completely filled pipe will, up to a point, increase sulphide generation.

Considering the major determining factors for sulphide build-up, an equation could be written that would express the rate of sulphide build-up as a function of the involving factors (i.e., pipe diameter, temperature, chemical oxygen demand (COD) and stream velocity). Three well-known equations have already been proposed for the forecasting of sulphide build-up in filled pipes [8-10]. However in the current study a novel and recent data-driven technique, evolutionary polynomial regression (EPR), is used to present a better and more reliable equation for sulphide build-up prediction. It is shown that the developed model is able to learn the complex relationship between the sulphide build-up problem and its contributing factors in the form of a function with a high level of accuracy. The developed model in this study will be compared with the existing conventional models to forecast sulphide build-up in sewer pipes.

3 Evolutionary polynomial regression (EPR) method

The use of data-driven techniques and in particular those based on artificial intelligence (AI) in modelling of engineering phenomena have drawn much attention from the scientific and research community in the past few decades. Several classes of the AI-based data-driven approaches such as artificial neural network (ANN), genetic programming (GP), and their variants such as GABNN, LGP, and MSGP have been used to model various engineering problems. Among these a recently developed technique called evolutionary polynomial regression (EPR) is proven to be capable of learning complex non-linear relationships from a large set of data, and it has many desirable features for engineering applications. The EPR technique has been successfully applied to modelling a wide range of complex engineering problems including stability of slopes; liquefaction of soils; landslide risk management; material modelling and many other applications in Civil and Mechanical engineering [28-33]. EPR is a hybrid data driven technique based on the integration of genetic algorithm (GA) and least square (LS) to create true or pseudo-polynomial models from observed data. A typical formulation of EPR can be expressed in the following equation [34]:

$$y = \sum_{j=1}^{m} F(\mathbf{X}, f(\mathbf{X}), a_j) + a_0 \tag{2}$$

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 $\mathbf{X}$ 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 (CD):

$$\mathrm{CD} = 1 - \frac{\sum_{\mathrm{N}} (\mathrm{Y_a} - \mathrm{Y_p})^2}{\sum_{\mathrm{N}} (\mathrm{Y_a} - \frac{1}{\mathrm{N}} \sum_{\mathrm{N}} \mathrm{Y_a})^2} \tag{3}$$

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 CD 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 [34].

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 [34]. However the single-objective EPR methodology showed some shortcomings, and therefore the multi-objective genetic algorithm (MOGA) strategy has been added to EPR [35]. 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 (Giustolisi & Savic 2009) . 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 [34-39].

4 Modelling sulphide build-up in filled pipes

Several empirical models for prediction of sulphide build-up have been proposed by research studies for filled sewers. Three models have been referred to by literature as well established sulphide build-up models for steady state condition in filled pipes [11, 12, 24]. The models are presented in Table 1.

In these models D represents diameter of pipe (m), T is temperature of the sewage (^{0}C), r is hydraulic radius (m), [BOD] is concentration of biological oxygen demand (mg/lit) and [COD] is concentration of chemical oxygen demand (mg/lit). These models have taken into consideration several factors influencing sulphide production within filled sewers. While Thistlethwayte's equation includes the stream velocity of the sewage and the sulphate concentration in the sewage, the equations developed by Pomeroy [8] and by Boon and Lister [10] do not take into account the effect of these parameters. Boon and Lister developed their equation by switching COD for BOD in order to achieve a model with better accuracy. The value of the coefficient in their equation also was reduced accordingly compared with the equation developed by Pomeroy [8]. The empirical nature of the equations and the difficulty in comparing the prediction capability between the equations has been previously commented upon by Holder [40]. After considering all the three models, Pomeroy [8] noted that more information is needed on the effect of the stream velocity. Holder and Hauser [13] also concluded that further research is required to properly delineate the effect of flow velocity on sulphide production rate. Recent works on sulphide build-up in sewer systems focus on dynamics and dynamic modelling of H_2S production [12]. Dynamic modelling of sewer systems is necessary when dealing with certain sulphide control strategies such as injection of chemicals (nitrate, oxygen or metal ions) to either prevent sulphide formation or to remove sulphide from sewage once formed [41, 42]. However, in most applications of sewer models including the wastewater aerobic/anaerobic transformations in sewers (WATS), models have generally been limited to sewer systems under steady-state conditions [12, 15, 43].

The data used in this study for modelling sulphide build-up in filled pipes includes all the data reported in [8, 10, 44]. Boon and Lister [10] selected a rising main with 22.86 cm diameter and 914 m length which conveyed sewage from a residential area. Sewage is pumped through a total height of 28m from the bottom of the sump to the top of the main, where it is discharged into a manhole and gravitates down a sewer. The data that they used to present their model included 28 measurements from this rising main. Data presented by Pomeroy [8] included 51 measurements taken from different sewer systems in industrial countries such as the USA, Australia and Germany. Their data was taken from sewers with a variety of pipe diameters and lengths. Delgado's research [44] on sulphide build-up in Spain also produced 12 measurements from a sewer system in steady state condition.

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, a statistical analysis was performed on the input and output parameters (Table 2) of the randomly selected training and validation sets. The aim of the analysis was to ensure that the statistical properties of the data in each of the subsets were as close to the others as possible and thus represented the same statistical population. Random combinations of training and testing data sets were chosen and the minimum, maximum, mean, and standard deviation were calculated for all the contributing parameters for the training and testing datasets for each case. To avoid extrapolation it was necessary to ensure that all parameters in testing data sets fell between the maximum and minimum values used in training data sets. From these combinations the one with the closest values of standard deviation and mean was chosen to be used in training and testing stages in the EPR model development process. In this way, the most statistically consistent combination was used for construction and validation of the EPR model.

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 functions, number of terms, range of exponents, etc. [34, 35]. 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 CD (Equation 3). 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/her judgement and knowledge of the problem. The results of the EPR were analysed based on the simplicity of the models and the CD values of both training and testing datasets. After analysis of different alternative models the following expression (Equation 4) was found to be the most robust model for the sulphide build-up.

$$\frac{d[S]}{dt} = 0.0135[COD]^{0.5}T^{0.5}D^{-1}u^{0.5} \tag{4}$$

Where $\frac{d[S]}{dt}$ is sulphide build-up rate (mg/l-hr), [COD] is chemical oxygen demand concentration (mg/l), T is sewage temperature (^{0}C), D is internal diameter of the pipe (m) and u is the velocity of the stream (m/sec).

The comparison between observed sulphide and predicted sulphide using Equation 4 for training and validation data are presented in Figures 1 and 2 respectively. A very good agreement between observed and predicted sulphide can be concluded from these figures. Figure 3 also illustrates the comparison between the model presented in this study by using the EPR model and the previous models presented by other researchers. Coefficient of determination (CD) obtained for the presented model is 84% while for the other models it is considerably less.

To investigate the effect of each parameter on the amount of sulphide build-up, a parametric sensitivity analysis is carried out. For this sensitivity analysis, the amount of sulphide build-up rate is calculated by changing the value for each parameter from its minimum to its maximum value while the values for other parameters are kept at their mean rate. Figures 4 to 8 show how variation of each parameter affects the rate of sulphide build-up. It can be seen that increase in [COD], temperature, detention time and stream velocity will increase the amount of sulphide production, while increase in sewer diameter will result in less sulphide production. For example when COD concentration increases from 100 to 1200 mg/l, sulphide production rate increases from 0.7 to 2.5 mg/l-hr. The increase in sulphide build-up as a result of temperature rise is less significant compared with [COD]. As illustrated in Figure 5, when temperature increases from 15^{0}C to about 30^{0}C, the sulphide build-up rate increases from 1.4 to 2 mg/l-hr. The changes in sulphide build-up rate due to changes of the stream velocity are more notable. Figure 6 shows that sulphide build-up rate increases to up to 3.2 mg/l-hr while the stream velocity changes from 0 to 1.32 m/s. The sulphide build-up predicted by Pomeroy [8] and Boon and Lister [10] does not change when the stream velocity is increasing. That is because their equations (Equations No. 1 and No.2 in Table 1) do not involve a parameter that represents the stream velocity. Figure 7 also shows how pipe diameter has an inverse effect on sulphide build-up rate. The figures also show a similar trend for sulphide build-up rate when using other equations. Hence, in general, it can be concluded that the results provided by the presented model in this study are in agreement with the previous studies in the field of sulphide build-up in filled pipes and in steady state condition and moreover the developed model in this study provides better prediction compared with conventional models.

6 Summary and conclusions

Hydrogen sulphide problems (corrosion and odour) are among the most challenging problems regarding sewer operation and maintenance. Having an accurate model to predict sulphide build-up during the design phase and operation of sewers is very helpful for optimum planning of repair and maintenance strategies in sewer systems. A recently developed method (evolutionary polynomial regression) was used to present a more accurate model for sulphide build-up in steady state condition of filled sewers. It was shown that the proposed model in this study can provide more accurate predictions for sulphide build-up in filled pipes compared with other existing models.

In order to investigate the influence of each contributing parameter on formation of sulphide build-up, a comprehensive sensitivity analysis was carried out. The results showed that while the sulphide build-up grows by increasing [COD], temperature, detention time and/or stream velocity, the sewer diameter has an inverse effect on sulphide build-up.

An interesting feature of EPR is the possibility of obtaining more than one model for a complex phenomenon. Selecting an appropriate objective function, assuming preselected elements (based on engineering judgement), and working with dimensional information enable refinement of final models. The developed model in this study can be improved as more data become available by re-training of the EPR using additional data. However, it should be noted that the EPR models should not be used for extrapolation, i.e. for new cases where one or more parameters fall outside the range of the parameters used in training, the predicted results should be taken with caution and allowance should be made for the uncertainty. Also, quality of the data could have an effect on the quality of the models. Although EPR has been shown to be effective in developing robust models based on data, the selection of the appropriate models should be based on engineering judgement to avoid selecting inappropriate models that may not conform to the physics of the problem being studied.

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