Risk assessment of sewer condition using artificial intelligence tools: application to the SANEST sewer system

V. Sousa, J. P. Matos, N. Almeida and J. Saldanha Matos

ABSTRACT

Operation, maintenance and rehabilitation comprise the main concerns of wastewater infrastructure asset management. Given the nature of the service provided by a wastewater system and the characteristics of the supporting infrastructure, technical issues are relevant to support asset management decisions. In particular, in densely urbanized areas served by large, complex and aging sewer networks, the sustainability of the infrastructures largely depends on the implementation of an efficient asset management system. The efficiency of such a system may be enhanced with technical decision support tools. This paper describes the role of artificial intelligence tools such as artificial neural networks and support vector machines for assisting the planning of operation and maintenance activities of wastewater infrastructures. A case study of the application of this type of tool to the wastewater infrastructures of Sistema de Saneamento da Costa do Estoril is presented.

Key words | artificial neural networks, risk assessment, sewer condition, support vector machines

V. Sousa (corresponding author)
J. P. Matos
N. Almeida
J. Saldanha Matos
Department of Civil Engineering, Architecture and GeoResources, Technical University of Lisbon – IST, Av. Rovisco Pais 1049-001 Lisbon, Portugal
E-mail: *vitor.sousa@ist.utl.pt*

INTRODUCTION

During the last decades there has been a trend to develop and implement formal wastewater infrastructure asset management systems, which have been gradually evolving from reactive to proactive approaches. One of the first proactive-based asset management systems was developed by the Water Research Centre, in which the defects observed during closed-circuit television (CCTV) inspections were rated in order to obtain a classification for the sewer condition. Originally, the approach was used only to manage the critical sewers (sewers that have very high economic consequences in case of failure). Nowadays, the growing awareness of the non-economic dimension of sewer failures expanded the application of this approach to the non-critical assets (Fenner & Sweeting 1999). This approach has been implemented worldwide, with minor adjustments introduced by national institutions and local municipalities (WRc 2001; NRC-CNRC 2004). More complex and comprehensive models have also been developed with the purpose of optimizing decisions and prioritizing interventions, by taking into account hydraulic, environmental, social and economic constraints (e.g., MARESS – Reyna 1993; RERAUVIS – RERAU 1998; CARE-S – CARE-S 2005). These approaches were developed to support rehabilitation interventions, but presently there is also a growing demand for conducting periodical sewer inspections in order to comply with legal requirements. This has led to the development of similar models assisting in the decisions of prioritizing the sewers for inspection (e.g., AQUA-WertMin – Baur & Herz 2002; SCRAPS – Hahn *et al.* 2002).

In order to implement a risk-informed approach to support rehabilitation or inspection decisions there is a need for estimating the evolution of the sewer condition (Korving 2004). However, the complexity of the phenomena underlying the structural and operational deterioration is not yet fully understood and the physical-based models developed so far are extremely limited (mostly to corrosion in concrete pipes). Therefore, the majority of the models developed are statistical-based. The major drawback of the traditional statistical approaches (e.g., regression) is the difficulty of determining the effect of the interactions between different sewer characteristics (e.g., material, diameter, age) in the sewer performance. Consequently, in most cases, these models only consider one (usually the age) or two of these characteristics (usually the age in combination with one of the others). Artificial intelligence tools are an alternative that can be used in classification and pattern identification problems such as

doi: 10.2166/wst.2013.758

this (Tran 2007). The present paper discusses the use of artificial neural networks (ANNs) and support vector machines (SVMs) to estimate the condition of sewers. The results are also compared with those obtained with discriminant analysis. The models were built using data from the periodic CCTV inspection program that has been implemented in the Sistema de Saneamento da Costa do Estoril (Costa do Estoril Wastewater System (SANEST)) since 2005.

SEWER CONDITION MODELLING

Depending on the type of output provided, the models for determining sewer conditions can be classified as deterministic or stochastic (Mehle *et al.* 2001). The former provide estimates in an absolute and exact format while the latter comprise some form of uncertainty/variability quantification associated with the estimate. The deterministic models are the most common, but in a risk-informed context it is important to evaluate the uncertainty of the estimates in order to determine the best option. Regarding the approach used, the models for predicting sewer conditions can be classified into empirical or mechanistic (Mehle *et al.* 2001). The empirical models use statistical tools and methods to obtain relations between known variables and the sewer condition based on historical records. These models entail an implicit assumption that the pattern of deterioration will remain the same in the future. The mechanistic models seek to represent the physical, chemical and/or biological phenomena that take place within the sewers and are relevant to explain their condition, requiring information and data that are not generally available or cannot be easily obtained. There is another class of models (expert-based models) that rely on expert opinion to define the relation between the inputs and the outputs. These models (e.g., MOSIMO – Sousa *et al.* 2009; SCRAPS – Hahn *et al.* 2002) were less explored and are seldom used, although for situations of information scarcity they may be the only viable option for estimating the sewer condition.

Empirical models, also called statistical models, are the most widely studied and are built from statistical analyses of: (i) operation and maintenance failure records (e.g., clogging; collapse); or (ii) condition classification based on inspection data (e.g., operational or structural condition classification using a rating protocol). These models rely on fitting mathematical formulations to observed data and can be divided into (Tran 2007): (i) function-based models; and (ii) data-based models. In function-based models the mathematical expressions relating the inputs with the outputs are pre-defined at the outset. In this case, the fitting operation seeks to determine the coefficients of the functions (relative weight of each input) that minimize the error between the observed and the estimated outputs. Data-based models have no pre-defined expression relating the inputs with the outputs, and the fitting operation simultaneously adjusts the relation between the inputs and the outputs and the relative weight of each input.

The focuses of the present paper are the ANNs and SVMs, which are machine learning techniques. These techniques have the ability to learn the patterns of the underlying process from past data, capturing the relationship between the inputs and the outputs. The resulting models are then able to predict an output given a new set of input variables from the vicinity of the training domain.

CASE STUDY

The SANEST sewer system

SANEST is an infrastructure close to Lisbon, covering the interception, conveyance and treatment of wastewater generated in part of the municipalities of Amadora and Sintra, and in the municipalities of Cascais and Oeiras. The SANEST system covers over 22,000 ha, serving 800,000 equivalent inhabitants. The system is characterized by a large interceptor, with a length of 24.7 km, stretching along the coastline from Linda-a-Velha to Cascais. The interceptor, which drains the wastewater collected by 20 trunk sewers representing a network of 120 km of sewers, discharges at the Guia wastewater treatment plant (WWTP), where the sewage is treated before being discharged into the Atlantic Ocean through a long sea outfall. The Guia WWTP is completely buried 30 m under ground and presents a non-conventional treatment process with different operation modes for summer and winter seasons. It treats 59.1 million m^3 of wastewater annually (http://www.sanest.pt/).

Data collection

To support the pro-active management of the sewer system, inspection programs have been carried out periodically since 2005 (2005–2006; 2009–2010). Presently, the sewers are being inspected for the third time with the support of a geographical information system containing detailed data of most sewers (diameter, depth, length, slope, material and age). For this study, data were collected from the reports of the first (2005–2006) and second (2009–2010) inspections of the Caparide, Castelhana, Marianas and Sassoeiros trunk sewers. The trunk sewers were selected for analysis by the team responsible for managing the SANEST sewer system because they are among the group with the highest defect rate. The data were screened to remove the sewer reaches with incomplete information, resulting in a sample of 25.4 km of sewers. The majority of the sewers are of polyvinyl chloride (PVC) (12,682 m), vitrified clay (VC) (4,370 m) and high-density polyethylene (4,102 m) pipes. A smaller amount of sewers are of Portland concrete, corrugated polypropylene and corrugated PVC pipes.

The sewer operational and structural condition classes were determined from the CCTV inspection results using the WRc (2001) rating protocol. The WRc rating protocol uses a scale ranging from 1 (best condition) to 5 (worse condition) and it rates the sewers based on the weight of the most severe defect in the sewer reach. Also, it differentiates whether the defect affects mainly the operational performance (indicating the probability of clogging) or the structural performance (indicating the probability of collapse) of the sewer (WRc 2001).

Model design

The software Statistica from StatSoft was used in the present research because it has the capability for building all types of models presented. Non-categorical inputs (diameter, depth, length, slope and age) were standardized (e.g., z_i = (sewer$_i$ depth − mean depth of all sewers)/standard deviation of the depth of all sewers) before being used in the models to prevent numerical instabilities that might arise from the differences in the scale and the range between the variables. The pipe material was coded from 1 to 6 in an inverse relation with the average age (e.g., 1 – VC pipes, the oldest pipes on average; 6 – corrugated PVC pipes, the newest pipes on average).

The objectives underlying the CCTV inspections of sewers are mainly to: (i) identify the sewers that are in a condition requiring intervention and assist in defining the best technical solution for that intervention; and (ii) identify the sewers that are in a condition level at which intervention may be required in the short/medium term to prevent failure. Consequently, two alternative approaches were used to reduce the number of condition classes used as outputs: (i) ALT A – the sewers were classified into three categories representing reaches that are in good condition and are expected to endure a long period before the next inspection (category 0 – sewers in condition 1 and 2), sewers that require a shorter period of time until the next inspection (category 1 – sewers in condition 3) and sewers that are failing and require intervention in the short term (category 2 – sewers in condition 4 and 5); (ii) ALT B – the sewers were divided into those that require intervention (category 2 – sewers in condition 4 and 5) and those which do not require intervention (category 1 – sewers in condition 1, 2 and 3). ALT A is applicable when a selective inspection program is to be implemented whereas ALT B is applicable when a periodic inspection program is in place. Overall, the combination of operational and structural conditions with ALT A and ALT B resulted in the definition of four classification cases for each sewer (Operational – ALT A; Operational – ALT B; Structural – ALT A; Structural – ALT B). The data set was randomly split into 610 sewers for training and 135 sewers for testing in order to ensure that the same cases were used for training and testing in the different methods.

Artificial neural networks

An automated heuristic approach was adopted to choose the best ANN configuration considering only one hidden layer with up to 50 neurons, for multilayer perceptron ANNs (MLP), and between 50 and 100 neurons, for radial basis function ANNs (RBF). Several activation functions were tested (exponential; sigmoid logistic; softmax; identity; hyperbolic tangent), both in the hidden and the output neurons of the MLP ANNs, using different training algorithms (gradient descent; conjugate gradient descent; Broyden, Fletcher, Goldfarb and Shanno (BFGS)) and error functions (CE – cross entropy; SOS – sum of squares). For each classification case 100 ANNs were developed and the five best cases compared. Table 1 summarizes the best ANNs obtained for predicting the operational and the structural condition considering ALT A and ALT B. The confusion matrixes of the best ANNs are presented in Tables 2 and 3 for ALT A and ALT B, respectively. The BFGS was always the best training algorithm but the error function and activation functions varied widely without significant performance differences (−5% to +1% for the training and −3% to +0.5% for the test). For the classification case of the sewers' structural condition according to ALT B, the corresponding ANN presented in Table 2 was used to evaluate the effect of the initial weights of the neuron connections. Randomly varying the initial weights of the neuron connections in 100 ANNs resulted in correlations ranging from 67 to 79%, for the train data (average = 73%), and from 72 to 84%, for the test data (average = 76%).

Table 1 | Best ANNs for predicting the operational and the structural condition considering ALT A and ALT B

			Correlation		Number of neurons		Activation function	
Classification case	**Train algorithm**	**Error function**	**Train**	**Test**	**Hidden layer**	**Output layer**	**Hidden layer**	**Output layer**
Operational – ALT A	BFGS	CE	61.80	66.67	15	3	Hyperbolic Tangent	Softmax
Structural – ALT A	BFGS	SOS	68.52	71.85	29	3	Hyperbolic Tangent	Sigmoid Logistic
Operational – ALT B	BFGS	CE	80.00	82.96	19	2	Sigmoid Logistic	Softmax
Structural – ALT B	BFGS	SOS	75.74	82.22	18	2	Sigmoid Logistic	Sigmoid Logistic

Table 2 | Confusion matrix of the best ANN for the test group (ALT A)

	Predicted (operational)				Predicted (structural)			
Observed category	**0**	**1**	**2**	**Correct/ incorrect**	**0**	**1**	**2**	**Correct/ incorrect**
0	7	2	3	58.3%/41.7%	5	1	0	83.3%/16.7%
1	11	49	4	76.6%/23.4%	7	55	11	75.3%/24.7%
2	12	13	34	57.6%/42.4%	5	14	37	66.1%/33.9%
Correct/incorrect	23.3%/76.7%	76.6%/23.4%	82.9%/17.1%	66.7%/33.3%	29.4%/70.6%	78.6%/21.4%	77.1%/22.9%	71.9%/28.1%

Table 3 | Confusion matrix of the best ANN for the test group (ALT B)

	Predicted (operational)			Predicted (structural)		
Observed category	**1**	**2**	**Correct/incorrect**	**1**	**2**	**Correct/incorrect**
1	85	14	85.9%/14.1%	75	12	86.2%/13.8%
2	9	27	75.0%/25.0%	12	35	75.0%/25.0%
Correct/incorrect	90.4%/9.6%	65.9%/34.1%	83.0%/17.0%	86.2%/18.8%	75.0%/25.0%	82.2%/17.8%

Support vector machines

In the present paper, only C-SVMs were used, where the capacity (C) is a coefficient that regulates the trade-off between training errors and prediction risk minimization. Contrary to the ANNs, the SVMs provide a means of comparing the generalization of different models. For the type of SVMs used in the present research, this can be achieved by comparing C. Higher C values lead to higher weights given to in-sample misclassifications and lower generalization of the machine. An automated trial and error approach was adopted for testing linear, polynomial, RBF and sigmoid kernels varying the respective parameter values. A five-fold cross validation was carried out varying the capacity from 0.01 to 1 with 0.1 increments. Linear, polynomial (degree = 2 to 4; gamma = 0.1 to 0.2; coefficient = 0 to 2), RBF (gamma = 0.1 to 0.2) and sigmoid (gamma = 0.1 to 0.2; coefficient = 0 to 2) kernels were used and the data set was randomly sampled each trial (80% for train and 20% for test), instead of using the fixed division. The overall classification accuracy was the same for all SVMs, with the use of the linear and RBF kernels leading to the lowest C (0.110). Using the RBF kernel with C = 0.110, SVMs were developed for each classification case using the data partition defined for comparison of the various approaches. The confusion matrixes obtained for ALT A and ALT B are presented in Tables 4 and 5, respectively.

Discriminant analysis

The discriminant analysis was performed to compare the machine learning techniques' performance with a more traditional statistical method. The confusion matrixes obtained are presented in Tables 6 and 7. The Wilks' Lambda was used to test the significant variables in each

Table 4 | Confusion matrix of the best SVM for the test group (ALT A)

Observed category	Predicted (operational) 0	1	2	Correct/ incorrect	Predicted (structural) 0	1	2	Correct/ incorrect
0	17	0	17	50%/50%	14	6	10	46.7%/53.3%
1	70	64	6	45.7%/54.3%	17	37	10	57.8%/42.2%
2	48	16	32	33.3%/66.7%	12	0	29	70.7%/29.3%
Correct/ incorrect	12.6%/ 87.4%	80.0%/ 20.0%	58.2%/ 41.8%	41.9%/58.1%	32.6%/ 67.4%	86.0%/ 14.0%	59.2%/ 40.8%	59.3%/40.7%

Table 5 | Confusion matrix of the best SVM for the test group (ALT B)

Observed category	Predicted (operational) 1	2	Correct/ incorrect	Predicted (structural) 1	2	Correct/ incorrect
1	83	11	88.3%/11.7%	80	7	92.0%/8.0%
2	18	23	56.1%/43.9%	32	16	33.3%/66.7%
Correct/incorrect	82.2%/17.8%	67.6%/32.4%	78.5%/21.5%	71.4%/28.6%	69.6%/30.4%	71.1%/28.9%

Table 6 | Confusion matrix of the discriminant analysis model for the test group (ALT A)

Observed category	Predicted (operational) 0	1	2	Correct/ incorrect	Predicted (structural) 0	1	2	Correct/ incorrect
0	12	6	12	40.0%/60.0%	4	11	2	23.5%/76.5%
1	15	37	12	57.8%/42.2%	0	56	14	80.0%/20.0%
2	12	0	29	70.7%/29.3%	0	27	21	43.8%/56.3%
Correct/ Incorrect	30.8%/ 69.2%	86.0%/ 14.0%	54.7%/ 45.3%	57.8%/42.2%	100.0%/ 0.0%	59.6%/ 40.4%	56.8%/ 43.2%	60.0%/40.0%

Table 7 | Confusion matrix of the discriminant analysis model for the test group (ALT B)

Observed category	Predicted (operational) 1	2	Correct/ incorrect	Predicted (structural) 1	2	Correct/ incorrect
1	84	10	89.4%/10.6%	79	8	90.8%/9.2%
2	17	24	58.5%/41.5%	30	18	37.5%/62.5%
Correct/incorrect	83.2%/16.8%	70.6%/29.4%	80.0%/20.0%	72.5%/72.5%	69.2%/30.8%	71.9%/28.1%

classification case and develop reduced models. In all cases, the sewer material, diameter length and depth were the only significant variables. The models considering all variables and the significant variables alone yielded similar results.

DISCUSSION AND CONCLUSIONS

The different methods yielded very similar overall results, achieving high accuracy for classifying the sewers according to the ALT B categories. Since the main goal of modelling the condition of sewers is to identify the sewer reaches that may need intervention, the ANNs provided slightly better results. However, this conclusion must not be considered definitive. Contrary to the SVMs and discriminant analysis, the ANNs' results depend significantly on various factors. In particular, they depend on the initial weights of the neuron connections because of the possibility of existence of local minima in the optimization function, as illustrated for the structural condition according to ALT B.

All models revealed more limited accuracy for estimating the sewers in worse condition. This may be due to reduced number of sewers in category 2 (condition class 4 and 5), but it can also be an indication that premature deterioration of sewer may occur due to specific events and/or local conditions. According to the SANEST management team, construction defects may also be an important reason for many of the misclassifications, but there is no information available to support either of these hypotheses. Eventually, in a near future this information may become available because some sewers are being rehabilitated or replaced and will be inspected in the next inspection programmes.

ACKNOWLEDGEMENTS

The authors acknowledge the SANEST for providing the data used in the study. The ICIST-IST Research Institute support, the Fulbright/FLAD grant supporting research at UCDavis, the Calouste Gulbenkian Foundation grant supporting research at Ryerson University and the grants SFRH/BD/35925/2007 and SFRH/BD/39923/2007 from the Portuguese National Science Foundation are also acknowledged.

REFERENCES

Baur, R. & Herz, R. 2002 Selective inspection planning with ageing forecast for sewer types. *Water Science and Technology* **46** (6–7), 379–387.

CARE-S 2005 Computer Aided Rehabilitation of Sewer Networks (CARE-S). Project Number EVK1-CT-2002-00106. http://care-s.unife.it/ (accessed 15 December 2006).

Fenner, R. A. & Sweeting, L. 1999 A decision support model for the rehabilitation of 'non-critical' sewers. *Water Science and Technology* **39** (9), 193–200.

Hahn, M., Palmer, R., Merrill, M., Andrew, B. & Lukas, A. 2002 Expert system for prioritizing the inspection of sewers: knowledge base formulation and evaluation. *Journal of Water Resources Planning and Management* **128** (2), 121–129.

Korving, H. 2004 *Probabilistic Assessment of Combined Sewer Systems*. PhD Thesis, Delft University of Technology, Delft, The Netherlands.

Mehle, J., O'Keefe, S. & Wrase, P. 2001 *An Examination of Methods for Condition Rating of Sewer Pipelines*. Center for Development of Technical Leadership, University of Minnesota, Minneapolis, USA.

NRC-CNRC 2004 *Assessment and Evaluation of Storm and Wastewater Collection Systems*. National Guide to Sustainable Municipal Infrastructure (InfraGuide), Ottawa, Canada.

Renya, S. 1993 *Optimal Planning of Sewer Systems Rehabilitation*. PhD Thesis, Purdue University, West Lafayeyette, USA.

RERAU 1998 Méthodologie de programmation de réhabilitation des collecteurs visitables. Projet National RERAU (Réhabilitation des Réseaux d'Assainissement Urbains), IREX – Institut pour la recherche appliquée et l'expérimentation en génie civil, Paris (in French).

Sousa, V., Ferreira, F., Almeida, N., Matos, J., Martins, J. & Teixeira, A. 2009 A simplified technical decision support tool for the asset management of sewer networks. *Water Asset Management International* **5** (1), 3–9.

Tran, H. 2007 *Investigation of Deterioration Models for Stormwater Pipe Systems*. PhD Thesis, Victoria University, School of Architectural, Civil and Mechanical Engineering Faculty of Health, Engineering and Science, Victoria, Australia.

WRc 2001 *Sewerage Rehabilitation Manual*. 4th edn, Water Research Center (WRc), Medmenham, England.

First received 2 July 2013; accepted in revised form 11 November 2013. Available online 23 November 2013