APPLICATION OF ARTIFICIAL NEURAL NETWORK TO ANALYSIS OF CAMPUS WATER PIPE FAILURE

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ABSTRACT

When a given water distribution network is proficiently installed, the most likely hitch that could result in limiting the discharge of its function is failure of any of the facilities. Pipes have suffered the worst heat in campus communities and hence, deserve unending attention. The selection of enabling maintenance planning and control technique for specific water network scenario and infrastructural (pipe) conditions is cardinal in the availability and sustenance of efficient water distribution. This paper explores the use of artificial neural network to analyse and manage water pipe failure in a Campus community. An illustrative example has been demonstrated with the dominant AMC pipe failure dataset obtained from a typical Campus community, namely; University of Nigeria Nsukka. The indices of performance employed in the model include the mean absolute error which was 0.004052 and coefficient of determination (0.99548) which represents a very good fit. Deterioration curves were used to elicit the relationship of the failure variables on failure span. The results show that there is a strong correlation between the pipeline failure variables with the failure span. The average pressure head was closely directly proportional to the time of next failure while the number of previous pipe failures is inversely proportional to the time of next failure. This revelation is an important milestone which goes to supplement the decision tools of the maintenance practitioners in the studied location and the likes.

Keywords: Water pipe failure, campus community, artificial neural network, deterioration curves, maintenance planning

1. Introduction

Pipelines constitute an ample share of the facilities employed in distributing usable water to various destinations in a water distribution network (WDN) globally. A typical WDN is mainly composed of water storage, collection and transportation facilities among others. The need to keep water in constant supply for domestic and industrial uses cannot be over emphasized. Success in constant water distribution warrants careful and informed decision on the factors which guarantee harnessing and dissemination continuity. When a given WDN has been proficiently installed, the most likely hitch that could result is failure of any of the facilities. Pipes have suffered the worst heat in many developing communities. Cardinal in water distribution sustenance effort is the selection of enabling maintenance culture for specific scenarios and infrastructural (pipe) conditions. The huge expenses and other inconveniences associated with WDN failures have turned many municipality authorities to seek preventive interventions (Kabir, et al. 2015). A methodology for mitigating the adverse impacts of WDN has been suggested by past researchers (Kapelan, et al. 2017, Jianga and Liua, 2017). A rapid response scheme that involves manipulation of all internal and external factors for quickest restoration of water supply to all the areas affected by pipe failure, prior to the pipe repairs, was seen as most appropriate. Rezaei et al (2015) lists the triggers of water pipe failures and stress the great importance of mastering the effect of specific factors. The presentation buttress the dynamic loading effects using lifetime burst records and explained the reasons behind pipe failure and pipe breakage. The outlined failures were analyzed using statistical methods. More recent work on impact of static and dynamic effects on pipeline failures exist (Farmania et al, 2017). Individual pipes with similar attributes like age, soil type and diameter were aggregated together and treated as clusters for failure prediction. Data used to validate the technique was taken from WDN in UK municipality. Water pipes can fail as a result of weakening effect of exceeding threshold values of the design parameters. Researchers have laboured on pipe failures of this mould in the past (Khalajestani et al, 2015). The authors study both geometric and material variables using multi-modelling technique, namely; combination of finite element analysis with artificial neural network (ANN). Pipe length and depth as well as circumferential position of the defective area had dominant effect on the limit pressure capacity. Other analytical approaches drawn from literatures were tested in the study.

Useful intervention strategy against water pipe failures can be obtained through establishing practical procedures for picking out failure initiation zones or early leakage detection along the pipe run. Non intrusive, non destructive testing techniques have been shown to assist in achieving early failures detection in pipes. Specifically, an experimental investigation of socket joint failure possibility using acoustic emission method followed by a classifier based ANN was fully implemented in literature (Li, et al. 2018). The estimation accuracy of the ANN was shown to range from 97.2% to 96.9%, with good results on other statistical indices. The introduction of monitoring sensors at strategic points in the pipe run alongside other techniques, intended to pick out early stage attacks that can gradually lead to failure has also been suggested (Palleti, et al. 2016, Kima et al, 2016). There have been significant research output on pipe and water mains break prediction by analytical (statistical and mathematical) approaches (Yamijala, et al. 2009, Kabir, et al. 2015, 2016, Scheidegger, et al. 2015,). It is unfortunate that many factors affect pipe failure. The analytical methods resort to making assumptions in order to handle the multi-factor problem of the failure causes (Oladokun and Shodimu, 2010). This makes real application of the models very difficult. Reports of application of neural network methodology to full analysis of water pipe failures remain very scanty. Although the procedure does not guarantee outright clairvoyance, especially because lack of data on WDN or pipe failure history still exist, there can be huge progress in determining when failures are most likely to occur, using the technique. Artificial neural networks can handle any number of input-output pair of data sets as well as many variables in predicting behaviour and patterns of physical systems.

It is noteworthy that majority of the existing models on water pipe prediction border on Cities, Municipalities and Provinces managed by state authorities. In particular, no study have addressed pipe failure prediction in any Campus community where water demand is most necessary and maintenance of water facilities are handled within the school management authorities. Improving the technical state of WDN within artificial intelligence based prediction, specifically; using artificial neural network promises to be important milestone in maintenance planning and control of water pipelines in such areas. This paper is an attempt to address the issue.

2. Materials and Methods

The proposed method embraces a framework that begins with identifying a representative Nigerian campus community with characteristic water pipe failure, that is common or surpass what obtains in its counterparts. Based on age of Institution which translates to time of WDN installation, independence on external management and size, University of Nigeria Nsukka (UNN), the first Nigerian University, was chosen as case study. The Campus lies between 6°50′47’’N 7°24′09’’E and 6°52’25’’N 7°26’13’’E with an average elevation of 438 m above sea level. The collection of data on historical pipe failures from the works services department (WSD) which encompasses the maintenance department commenced after identification of a candidate Campus. Table 1 presents the most significant factors affecting water pipeline failures as obtained from the WSD. There were interview sections, extensive consultations with all UNN water stake holders as well as constructive opinion surveys to fish out the most relevant variables in tandem with UNN water pipeline peculiarities contained in Table 1, which would be most appropriate for the study. Table 2 presents the results of the consultations. The cumulative total length of the pipes was about 28,200 kilometres as abstracted from Physical Planning Unit (PPU) records. The basic assumption that the data was correct as collected had to be made as there was no further evidential headway available. In the second stage, the collected data were sorted and described statistically based on pipe characteristics and contribution to cumulative failures recorded within each of the ten (10) year data base (2005 – 2015) used for the study. The initial statistical analysis revealed that majority of the failures occurred in pipes made of Asbestos and Cement mortar. In particular, majority of the pipes installed at the inception of the University belong to the group. It was observed that replacements with pipe of other materials, upon failure of AMC have become part of the maintenance culture. The third step was the pre-processing and partitioning of the AMC pipe failure data for use in ANN prediction. The most suitable ANN architecture was selected after series of trials. Two thirds of the data was used for training and validation while the remainder was used to test the network. Finally, deterioration curves were plotted to ascertain the impact of each factor on the failure time and to predict the next period to expect failure in the water pipeline.

Table 1: Sub groups of some factors that can influence water pipeline failures

Physical Factors	Environmental Factors	Interior Factors	Maintenance Factors
Topography of pipe location	Type of Soil	Water velocity	Failure time
Diameter	Loading	Water pressure	Repair time
Length	Groundwater	Water quality	Failure location
Year of construction	Temperature	Internal corrosion	Failure type
Pipe material	External corrosion		Failure history
Joint method	Other networks		
Internal protection	Leakages		
External protection			
Pressure class			
Wall thickness			
Laying depth			

Table 2: Prediction Variables used for the study

Type	No	Purpose description	Range of variation	Source
Input	2	Pipe material	AMC	Physical planning unit
	3	Pipe diameter	20 – 250mm	Physical planning unit
	4	Pipe length	50 – 1050.66m	Physical planning unit
	5	Pipe thickness	3.4 – 4.17mm	Physical planning unit
	6	Pipe location	Heavy (1), Moderate (2) and Light (3)	Manually done with the street layer in GIS
	7	Average pressure head	0 – 72.855m	EPAnet software
	8	Water velocity	0 – 4.17m/s	EPAnet software
	9	Pipe installation year	0 – 25years	
	10	1st failure occurrence	0 – 25years	Works Department

	11	Number of previous failure	0 – 12 failures	Works Department
Output	1	Next time to failure		

3. Neural network prediction

The implementation of neural network prediction methodology to analyse real reliability problems has found successfully application by researchers (Ozor, et al. 2017). NeuroSolutions offers neural network modelling products, training, support, and custom solutions for a wide range of applications (Neuro-Dimension, 2015). Many algorithms can be used, but back propagation processes are popular for fast convergence capabilities. The ANN produces an output which it compares to the target output, then systematically backtracks and alters the weights until the network's mean squared error is minimised. The basic step in using the approach dwells in availability of a large amount of data and selection of a suitable architecture for training and validation.

3.1 Model development

The datasets obtained for the AMC water pipeline failures were used to train an ANN for the failure prediction, based on the factors affecting the WDN (Table 2). The factors shown in Table 2 were used to build the models. The data were first normalized in line with the steps reported elsewhere (Ozor et al, 2017, Ertas and Jones). In particular, the procedure allows all the data to be squashed between 0 and 1 so that the neural network tool in MATLAB software can accept it. Equation (1) was used to achieve the data normalization. The data was subsequently partitioned into three sets. Two thirds were used for training and validation while a third was used for testing.

$$pn = \frac{2(p - p_{min})}{p_{max} - p_{min}} - 1 \quad (1)$$

Where:
Pn = normalized data
P = data value
$P_{\min}$ =minimum value in the data set
$P_{\max}$ = maximum value in the data set

3.2 Network architecture

The inputs to the ANN can be referred to as predictors whereas only single output was identified. It can be called the next time of failure. As still practiced in ANN field, selection of the best architecture is done on trial and error basis. Several architectures were tried until the most suitable one surfaced. That is; a feed-forward back propagation (FFBP) which approximates most data sets arbitrarily well as well as the Levenberg Marquardt training algorithm. Figure 1 presents the neural network model. It has ten input and hidden layers apiece, one output layer and an output. The measure of efficiency employed for the study was route mean square error and mean square error represented by equation (2) and (3). The values obtained for each were 0.698018 and 0.445158 respectively. The minimum absolute error was 0.004052 while an error goal of 0.0 was targeted. The coefficient of determination can be unity for a faultlessly simulated data or perfect relationship. It can be represented by equation (4). The closer it gets to unity, the better the prediction accuracy of the ANN.

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}\sum_{i=1}^{m}(d_{ji} - p_{ji})^2}{nm}} \quad (2)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - s_i)^2 \quad (3)$$

$$R^2 = \frac{\left(\sum_{j=1}^{n}(d_j - \bar{d})(p_j - \bar{p})\right)^2}{\sum_{j=1}^{n}(d_j - \bar{d})^2 \cdot \sum_{j=1}^{n}(p_j - p)^2} \quad (4)$$

Where:
d_{ji} = ith component of the output for the jth pattern;
p_{ji} = ith component of the fitted output from the network for the jth pattern;

$\bar{d}$ and $\bar{p}$	= average of the desired output and predicted output respectively
n and m	= number of patterns and the number of variable outputs respectively,
s_i and t_i	= network output values and the target outputs respectively
N	= number of samples presented to the network for the training exercise

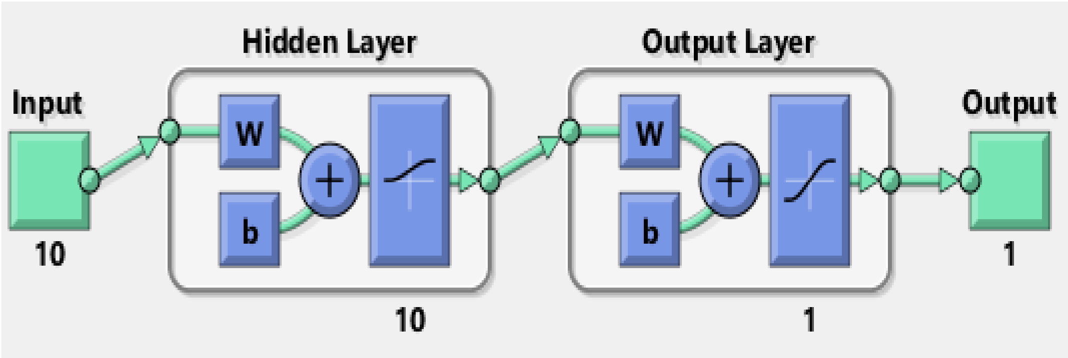

Fig 1: Architecture of the proposed neural network

3.3 Model validation

Finally, the network performance has to be examined for possible changes in the training process; training algorithm, network architecture or the underlying data sets. The training record is first observed closely and regression plots created, upon satisfaction with the training result. The essence of the regression plot is to study the relationship between the outputs-target nexus. If network outputs and targets are not exactly equal, some differences will be observed irrespective of magnitude. A plot of the regression coefficient was relied upon to determine how well the model correlates the real data. Figure 2 presents the regression plot.

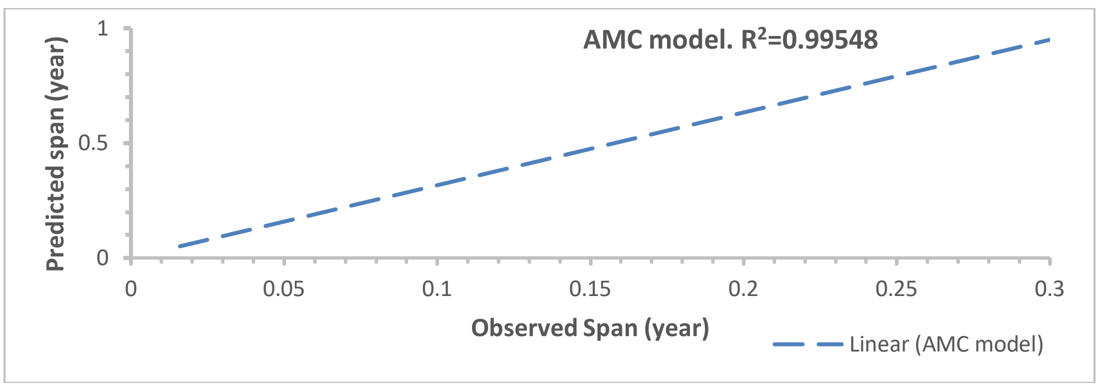

Figure 2: Regression plots of the predictive model

3.4 Deterioration Curves

The impact of each factor on the failure time can be expressed graphically. Accordingly, deterioration curves were developed for the model and presented in figure 3 through 4. The deterioration curve gives a better appreciation of the pipe failure span and the failure variable nexus. The variables were divided into two to aid understanding and reduce complexities. In the first group, only variables that offer positive impact on the pipe failure span were presented. The variables are pipe location, pipe diameter, pipe thickness, year of pipe installation, pipe material, year when the first failure occurred on pipe and the average pressure. The second group shown in figure 4 is where those variables that have a negative impact on the failure span are displayed.

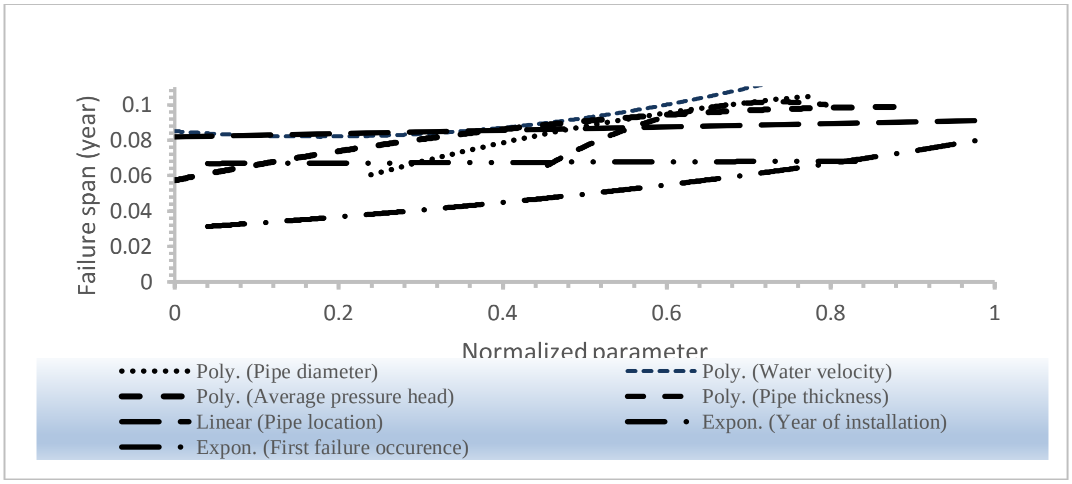

Figure 3: AMC model deterioration curves - directly proportional factors

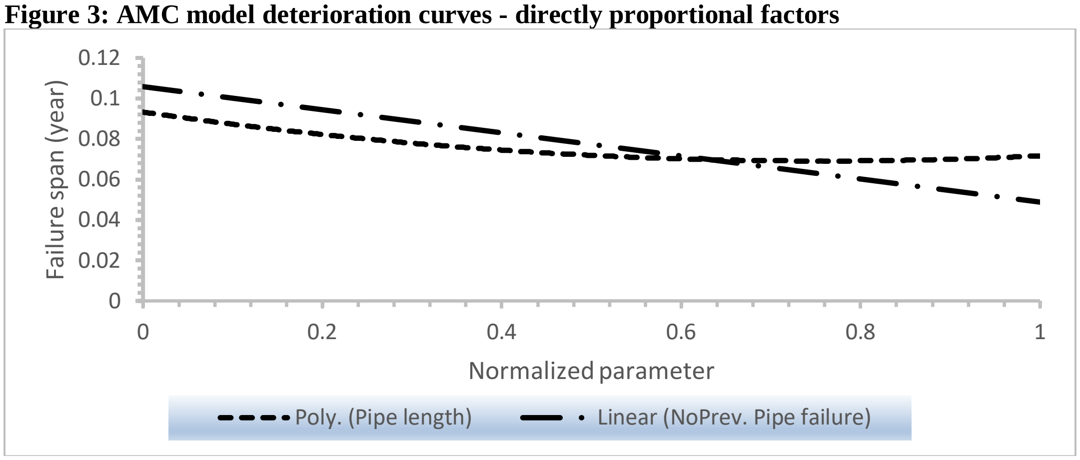

Figure 4: AMC model deterioration curves - inversely proportional factors

4 Results and Discussion

The prediction of water pipeline failure by the neural network approach as undertaken in this study can be said to be simple, precise and at worst good practice. The neural network was able to take all the input variables presented to it without complex mathematical rigours and assumptions encountered in analytical methods. The indices of performance of the network were all within acceptable values. For example, the regression value obtained (0.99548) means that the ANN predicted the failures very well. The very low value of the error goal is quite characteristic of a good predictive result. The results of figure 3 and figure 4 show that there is a strong correlation between the pipeline failure variables with the failure span. For instance, from figure 3, the average pressure head for the AMC pipe appears to be directly proportional to the time of next failure. A similar relationship also exists for the year of pipe installation. In a similar development, for the negative variables, it is evident in figure 4 that the number of previous pipe failures is inversely proportional to the time of next failure. This revelation is an important milestone which goes to supplement the decision tools of the maintenance practitioners. Hence, the approach employed in this study has lead to the presentation of a water pipe failure prediction methodology for Nigerian Campus communities. However, there could be other areas of expansion of the study, such as the inclusion of other factors in the subgroups presented in Table 1 to ascertain what the results will be. Future research efforts in the area can be directed towards the omission.

5. Conclusion

This study has satisfied its main cleavage of presenting a management and control strategy for water pipeline failure prediction using artificial neural networks. The methodological steps has been carefully explained and exemplified with data obtained from a typical campus community, namely; University of Nigeria Nsukka. The results were displayed in understandable graphs as well as explained very well. The result shows that though water average pressure head and number of previous failures posses opposite impacts on the failure span of AMC water pipes, the relationship of both variables with failure span can provide a good means of estimating future failure time of the pipes. The result also shows that the ANN approach is a good means of predicting water pipeline failures. Interestingly ample data was available for the illustrative application. The validation of the developed model on unseen data equally showed good performances. The ANN approach can predict the time of next failure on an AMC pipe in the water network. The dataset can further be expanded with experimental or field data.

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Biographies

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