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

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ABSTRACT
Pipes have suffered the worst heat in water distribution network failures and hence, deserve unending attention. The selection of enabling maintenance planning and control technique for specific water network scenario and varying 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 in South East Nigeria. 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 personnel and field technicians alike.

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

1. Introduction
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. Pipelines constitute an ample share of the facilities employed in distributing usable water from its source 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 various 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 artificial neural network methodology to complete analysis of water pipe failures remain very scanty. Although the procedure does not guarantee outright or perfect clairvoyance, especially as lack of accurate 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 ANN 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 contribute to the challenge of water pipe failures and maintenance planning in Campus communities.

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 can translate to time of WDN installation, independence on external management and Campus size, University of Nigeria Nsukka (UNN), the first indigenous 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 or confirmatory 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 in 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

<table>
<thead>
<tr>
<th>Physical Factors</th>
<th>Environmental Factors</th>
<th>Interior Factors</th>
<th>Maintenance Factors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topography of pipe location</td>
<td>Type of Soil</td>
<td>Water velocity</td>
<td>Failure time</td>
</tr>
<tr>
<td>Diameter</td>
<td>Loading</td>
<td>Water pressure</td>
<td>Repair time</td>
</tr>
<tr>
<td>Length</td>
<td>Groundwater</td>
<td>Water quality</td>
<td>Failure location</td>
</tr>
<tr>
<td>Year of construction</td>
<td>Temperature</td>
<td>Internal corrosion</td>
<td>Failure type</td>
</tr>
<tr>
<td>Pipe material</td>
<td>External corrosion</td>
<td></td>
<td>Failure history</td>
</tr>
<tr>
<td>Joint method</td>
<td>Other networks</td>
<td></td>
<td>Service crew</td>
</tr>
<tr>
<td>Internal protection</td>
<td>Leakages</td>
<td></td>
<td>Spare parts</td>
</tr>
<tr>
<td>External protection</td>
<td></td>
<td></td>
<td>Design life</td>
</tr>
<tr>
<td>Pressure class</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wall thickness</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Laying depth</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Prediction Variables used for the study

<table>
<thead>
<tr>
<th>Type</th>
<th>No</th>
<th>Purpose description</th>
<th>Range of variation</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input</td>
<td>2</td>
<td>Pipe material</td>
<td>AMC</td>
<td>Physical planning unit</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>Pipe diameter</td>
<td>20 – 250mm</td>
<td>Physical planning unit</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>Pipe length</td>
<td>50 – 1050.66m</td>
<td>Physical planning unit</td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>Pipe thickness</td>
<td>3.4 – 4.17mm</td>
<td>Physical planning unit</td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>Pipe location</td>
<td>Heavy (1), Moderate (2) and Light (3)</td>
<td>Manually done with the street layer in GIS</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>Average pressure head</td>
<td>0 – 72.855m</td>
<td>EPANET software</td>
</tr>
<tr>
<td></td>
<td>8</td>
<td>Water velocity</td>
<td>0 – 4.17m/s</td>
<td>EPANET software</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>Pipe installation year</td>
<td>0 – 25years</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>1st failure occurrence</td>
<td>0 – 25years</td>
<td>Works Department</td>
</tr>
<tr>
<td></td>
<td>11</td>
<td>Number of previous failure</td>
<td>0 – 12 failures</td>
<td>Works Department</td>
</tr>
<tr>
<td></td>
<td>1</td>
<td>Next time to failure</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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). Neuro Solutions 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, 1996). 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 (Ozor et al., 2017, Rajpal et al., 2006). The data was subsequently partitioned into three sets. Two thirds were used for training and validation while a third was used for testing.

\[
p(n) = \frac{2(p - p_{\text{min}})}{p_{\text{max}} - p_{\text{min}}} - 1
\]

Where:
- \( P(n) \) = normalized data
- \( P \) = data value
- \( p_{\text{min}} \) = minimum value in the data set
- \( p_{\text{max}} \) = 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 is 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) neural network, 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 root mean square error and mean square error represented by equation (2) and (3) respectively (Rohani et al., 2011). 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.

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

\[
\text{MSE} = \frac{1}{N} \sum_{i=1}^{N} (t_i - s_i)^2
\]

\[
R^2 = \frac{\sum_{j=1}^{m} (d_{j} - \bar{d})(p_{j} - \bar{p})^2}{\sum_{j=1}^{m}(d_{j} - \bar{d})^2 \sum_{j=1}^{m}(p_{j} - \bar{p})^2}
\]

Where:
- \( d_{ji} \) = \( i \)th component of the output for the \( j \)th pattern;
- \( p_{ji} \) = \( i \)th component of the fitted output from the network for the \( j \)th 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

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.
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.
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 difficulty 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 roughly directly proportional to the time of next failure. A similar relationship also exists for the year of pipe installation. The water velocity seems to be the most proportional factor in figure 4. It will be reasonable to think that a useful relationship exists between the variable and the time of failure. However, some restraint should be exercised in using the variable as a decision tool in the pipe maintenance because the studied location is located in a hilly area where most of the water distribution is by gravity method. Water is pumped to a reservoir on top of a hill inside the Campus and distributed through pipes. The incremental velocity of water along the pipe run may not be unconnected with significant height differential between the upstream and downstream sections of the pipes. Both the first failure occurrence and year of installation belong to the factors that present proportional relationship with the failure span. The failures that are most likely going to occur due to pipe age can be addressed within the pipe design period. The
maintenance action in this case is that the pipe should not be allowed to be in service after its design life, irrespective of state. With this precaution in mind, pipe failures due to age or time of installation is not likely within the service life. The first failure occurrence time, though a variable that possess somewhat proportional relationship with failure span in figure 3, may not provide a standalone maintenance direction to the maintenance personnel. This is especially if the failure occurs within the service life of the pipe. The cause of the failure must be investigated further since the pipe is not expected to fail as a result of when it was first installed, given that the installation is proficiently implemented. Pipe thickness and pipe location are variables whose failures are pressure related. Therefore, with necessary adjustment of the average pressure in the pipes in line with the allowable pressures in concerned pipes and locations, failures occurring from the two variables can be checked. The foregoing can lead to the conclusion that the most significant maintenance variable among the roughly proportional factors considered in the studied location is the average pressure head.

In a similar development, for the negative variables, it is evident in figure 4 that the number of previous pipe failures is approximately inversely proportional to the time of next failure. A careful observation of figure 4 reveals that the relationship of number of previous failures is not purely inversely proportional to the failure time, compared to that of pipe length. What actually obtains is a situation where there is a significant decrease in number of previous failures, then a period where the variable assumed a constant state before a point of inflection, when it started increasing. If the pipes are installed according to the design of the water distribution network, figure 4 shows that the number of failures will be reduced at the infant stage. The situation can change later in its life, with attendant increase in number of failures. The maintenance personnel should be aware of this relationship in other to take care of any eventuality. The pipe length has a continuous negative relationship with failure span in this study. It is possible for the variable to have effect on failure if proper care is not taken to install the pipes according to the water distribution network design. 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 led 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 challenge.

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 possess 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

Dr Paul A. Ozor obtained a bachelor’s degree (B.Engr) in Mechanical/Production Engineering at Enugu State University of Science and Technology, Nigeria in 2001. He worked as project manager with some engineering companies before proceeding to Department of Mechanical Engineering, University of Nigeria Nsukka (UNN), where he specialized in Industrial Engineering and Operations Management. He obtained both Masters and PhD degrees in 2008 and 2015, respectively from UNN. Dr Ozor is a TWAS-DST-NRF fellow to University of Johannesburg, South Africa, and had been awarded the Association of Common Wealth Universitie’s (ACU) early career scholarship in 2014. His research interests include Industrial Operations modelling, Systems Analysis, Reliability Engineering, with special emphasis on Maintenance, Failure mode effects and criticality analysis (FMECA), Safety and Risk assessment (SRA) as well as Environmental influence modelling, including climate change effects on water, waste and energy nexus.

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Professor Charles Mbohwa is currently the Ag, Executive Dean of Faculty of Engineering and the Built Environment, University of Johannesburg. He obtained B. Sc Honours in Mechanical Engineering in 1986 from Department of Mechanical Engineering, University of Zimbabwe, Harare, Zimbabwe. He later bagged M. Sc. in Operations Management and Manufacturing Systems in 1992, with a distinction from Department of Manufacturing Systems Engineering, University of Nottingham, UK. He obtained PhD in Engineering (Production Systems focusing on Energy and life cycle assessment) from Tokyo Metropolitan Institute of Technology, Tokyo, Japan in 2004. Professor Mbohwa is an NRF-rated established researcher. In January 2012 he was confirmed as an established researcher making significant contribution to the developing fields of sustainability and life cycle assessment. In addition, he has produced high quality body of research work on Southern Africa. He is an active member of the United Nations Environment Programme/Society of Environmental, Toxicology and Chemistry Life Cycle Initiative, where he has served on many taskforce teams. He has published over 200 research articles in leading international Journals and had been keynote speaker in many international conferences despite supervising many postgraduate students and postdoctoral fellows.