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3D Interactive Modeling of Pipe Failure in Water Supply Systems

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Abstract: The increased incidences of pipe breaks worldwide are posing a serious threat to potable water security in urban communities. The consequences may involve water loss and service interruptions, compromised water quality, infrastructure disruptions, and loss of revenue. Thus, creating failure assessment models is quite crucial to sustain water distribution networks (WDNs) and to optimize maintenance spending. This research paper aims at developing an assessment framework for water systems, as well as modeling the failure phenomena toward sustainable management of underground infrastructure. The city of El Pedregal in Peru was chosen to exemplify the methodology of the research due to the rapid pace of urbanization and growing economic activities in the region, which make water infrastructure even more critical. The framework is based on the application of modeling techniques stemming from statistical regression analysis (RA) and 3D schematic representation. First, the influential factors that lead to the deterioration of the WDNs are determined. Second, the RA technique is leveraged to evaluate and model the failure rate through consecutive simulation operations and a 3D surface plot. Finally, the efficacy of the model is investigated using different performance metrics, in conjunction with a residual analysis scheme. The validation results revealed the robustness of the model with R-squared (R^2) and the sum of squares error (SSE) of 0.9767 and 0.0008, respectively. The developed model is a predictive tool that can be used by municipal engineers as a preemptive measure against future pipeline bursts or leaks.

Keywords: *deterioration, water infrastructure, regression analysis, sustainability, condition assessment*

Water supply systems are integral elements of underground infrastructure and indispensable constituents for urban communities (Folkman 2018; Dawood et al. 2019a). Recurrent incidents of water main breaks are long-standing problems all over the world, causing water loss and floods, interrupted access to safe drinking water, compromised water quality, damage to the surrounding civil structures, disruptions to businesses, and loss of revenue (Harvey et al. 2014). The American Society of Civil Engineers (ASCE) 2017 report card estimated a daily water loss of six billion gallons due to pipe leakages, with yearly water main breaks totaling 240,000 in the United States. This water loss could support 15 million households per day, which equates to approximately 14% to 18% of treated potable water. Moreover, the report recorded that pipe break rates escalated by 40% between 2012 and 2018 in North America (ASCE 2017). Consequently, the American Water Works Association estimated one trillion dollars is required for U.S. water infrastructure over the next 25 years (AWWA 2012).

The image is not different in Latin America, where it enjoys an abundance of water resources. The region includes some of the largest lakes in the world, such as Titicaca in Peru, as well as four of the world's 25 largest rivers. Additionally, the Amazon Basin supplies 20% of the total runoff of the world's fresh water. However, in most of Latin America's big cities, more than 50% of the treated water is lost due to leaky pipes. This rate might escalate up to 90% in some congested cities (Barlow and Clarke

2007). Faced with this litany of growing risk of pipe failure in Latin America, the burden has increased on water utilities to ensure safe and reliable water services (Dawood et al. 2019a). This research work is relevant to water resources management in Latin America because of the significance of prioritizing infrastructure investments as an engine for growth, as well as saving money and water resources in this developing world. This emphasizes the need for condition assessment models capable of assisting the decision-makers in the prioritization of replacement and/or rehabilitation procedures of underground water systems (Kleiner and Rajani 2001a; Dridi et al. 2009), especially during the economic recession that minimized the funding policies.

Substantial efforts have been found in the literature to evaluate the water pipe deterioration and model its risk of failure. Many of these efforts adopted statistical-based approaches, while others focused on artificial intelligence and soft computing methods to develop failure prediction models. Statistical models are created from historical data that link pipe attributes, operational factors, environmental factors, and frequencies of pipe breaks (Kleiner and Rajani 2001b). Such models are based on collecting long-range data pertaining to past pipe bursts and applying the regression analysis (RA) techniques to process the data (St. Clair and Sinha 2012). Generally, statistically-derived models are classified into two categories: deterministic and probabilistic. Statistical deterministic models are known as time-dependent models. Examples of these models can be found in (Shamir and Howard 1979; McMullen 1982; Walski and Pelliccia 1982; Jacobs and Karney 1994). Whereas, probabilistic statistical models utilize the probability theory and uncertainty to estimate the likelihood of pipe failures. Examples of such models may be found in (Jeffrey 1985; Constantine et al. 1996; Mavin 1996; Deb et al. 1998).

The objective of this paper is to develop a methodology for the deterioration evaluation of water distribution networks (WDNs), in addition to modeling their failure rates. The proposed methodology is grounded in the RA technique by utilizing the embedded statistical package of *MATLAB © R2019b*.

Background

Regression Analysis

RA is a set of statistical procedures for analyzing and modeling the relationships between two or more variables. Hence, predicting the response variables from predictor variables. The most common form of this relationship is linear regression, which is expressed in Equation (1) (Chatterjee and Hadi 2012):

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i \tag{1}$$

where, Y_i is the response variable in the *i*th trial, β_0 and β_1 are the model regression coefficients, X_i is the predictor variable in the *i*th trial, and ε_i is the random error.

The generic form of this relation is attained when there is more than one predictor variable, and the generated model is called a multiple regression. This relationship is presented in Equation (2) (Kutner et al. 2005).

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + ... + \beta_{p-1} X_{i,p-1} + \varepsilon_i \tag{2}$$

Generally, the regression coefficient values β_0, β_1, β_2, etc., in Equation (2) are unknown and must be calculated from the available data. Because no previous information exists about the form of regression relationship (e.g., linear or curvilinear) and the appropriate predictor variables, it is quite essential to analyze the data in order to develop a proper regression model.

There exist several methods to check the forms of linearity by observing the curvatures in different plots, such as looking at the scatterplot of residuals as opposed to the fitted values. Moreover, checking the scatterplot of residuals against each predictor. If the scatterplot proposes a curvilinear relationship, it means this is a polynomial regression model. The mathematical definition of this model is postulated in Equation (3) (Kutner et al. 2003):

$$Y_i = \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2}^{\ 2} + ... + \beta_h X_{i1}^{\ h} + \varepsilon_i \tag{3}$$

where, *h* is the degree of the polynomial equation, and the relationship is called quadratic when *h* = 2, cubic when *h* = 3, quartic when *h* = 4, and so forth. Although the polynomial regression fits a non-linear relationship between the response variable and the predictor variable, it is recognized as a linear regression model.

Literature Review

Several endeavors have emerged recently as a step toward the evaluation and modeling of water pipe failure rates using different statistical and machine learning techniques. For example, in the statistical modeling of water infrastructure, Wang et al. (2009) proposed five multiple regression models for the evaluation of break rates in the water supply system, after considering a multitude of factors (i.e., pipe diameter, length, material, year of installation, and cover depth). Asnaashari et al. (2009) applied multiple regression, together with Poisson regression, to develop two failure prediction models based on ten years of historical data. They then compared the performances of the two models and found that the Poisson model revealed superior prediction results. In the artificial neural networks (ANNs) domain, Sattar et al. (2019) constructed an extreme learning machine (ELM) model to forecast water pipes' failure and to optimize maintenance and/or rehabilitation operations. Notwithstanding the high accuracy of the ELM model, its practicality was limited due to missing pipe break records. Dawood et al. (2019b) leveraged the ANNs and pattern recognition techniques to predict the risk of water quality failure in Peru. Christodoulou et al. (2010) trained an ANNs model, then analyzed the risk associated with buried pipes via a survival analysis approach. In the fuzzy logic modeling, Fayaz et al. (2018) introduced a hybrid approach through the fusion of the Kalman filter and the Hierarchical Fuzzy Logic. Their approach aimed at improving the risk assessment in the water piping system. Malinowska (2017) integrated the geographic information system (GIS) and a fuzzy inference system (FIS) to predict the pipeline failure hazards in a mining field. The model validation showed a good correlation between the predicted and observed results. Li and Yao (2016) used the Analytic Hierarchy Process (AHP), in conjunction with fuzzy logic to estimate the risk of failure of long water mains. In the boosting algorithms applications, Winkler et al. (2018) designed a boosted decision tree model that is based on machine learning algorithms to address the deterioration and failure mechanisms in WDNs. Later, the model performance was evaluated through confusion matrices and receiver operating characteristic curves. Some researchers combined the statistical and machine learning techniques to develop their methodologies. For instance, Fahmy and Moselhi (2009) presented a framework that involved the multiple regression technique, multilayer perceptron ANNs, and general regression neural network to predict the remaining useful life of water pipes in North America. Their model was designed on the basis of several factors, including physical, mechanical, operational, and environmental factors. Tabesh et al. (2009) incorporated three data-driven modeling techniques, i.e., ANN, neuro-fuzzy systems (NFS), and multivariate regression (MVR), to assess the risk of failure of water mains and mechanical reliability. The ANN model outperformed the NFS and MVR models in assessment capability and performance. Najjaran et al. (2004) developed a fuzzy expert system capable of modeling the deterioration of metallic pipes based on surrounding soil properties. Their system was built using expert knowledge and field information and through the fusion of linear regression and FIS. Aydogdu and Firat (2015) combined three machine learning techniques (least squares support vector machine, feed-forward neural network, and generalized regression neural network) to develop a methodology for estimating the failure frequency in water infrastructure. These studies mainly focused on the computational modeling of breaks and risk of failure. Nevertheless, a 3D interactive representation that reveals the severity of failure in WDNs was never performed. Therefore, the intellectual contribution of this study is to bridge the gap by addressing the aforementioned limitation using simulation and RA.

Study Area

In order to recognize the failure patterns and develop the water mains failure model, seven years of historical data related to pipe characteristics and breakage rates were obtained from the WDNs of the city of El Pedregal, Peru. Figure 1 shows the geographical location of this city on Google Earth. El Pedregal is a city in the Arequipa Region in southwestern Peru with elevation 1,410 m above sea level. It is located 70 km west of the city of Arequipa in the arid coastal plain of Peru. The land in that district is partially for irrigated agriculture and the rest for desert vegetation. According to the 2017 census, the city had 44,264 inhabitants, showing an increase in population by more than double since 2007. The city of El Pedregal makes a unique case study because of the following reasons: 1) rapid increase of urbanization as a result of rural-urban migration; 2) growing economic activities in the region that promote social welfare; and 3) criticality of water infrastructure in this developing region, where the majority of population live in an extremely water scarce environment. The growing population and the rapid pace of urban sprawl has hindered the municipalities to provide infrastructure and services to the growing number of residents. Hence, the investment in water infrastructure is quite crucial as it is the engine for growth in the region (The World Bank 2018).

The economic prosperity in the Arequipa Region is the driving force behind the population growth, especially after implementing the Majes Irrigation Project, which has transformed 15,000 hectares of the desert to fertile land. The area is projected to receive new developments, such as the new dam that will be constructed in the second phase of the project in order to expand the area of irrigated land and boost the region's profit through the export-oriented agribusiness (Stensrud 2016).

The water supply system of El Pedregal was constructed in August 2012. Figure 2 illustrates laying the Polyvinyl Chloride (PVC) pipes as part of the construction process in El Pedregal. The main network consists of 6,482 m of PVC pipes with diameters ranging from 110 mm to 500 mm. In contrast, the secondary network has 11,129 m of PVC pipes with diameters ranging from 63 mm to 90 mm. The pipe characteristics of both networks (i.e., primary and secondary) were collected, classified, and analyzed. A sample of the obtained data is depicted in Table 1.

Objectives and Methodology

This paper addresses two substantial issues pertaining to the management of urban water networks, namely, the deterioration modeling and failure frequency assessment. To highlight these issues, it is imperative to study and determine the factors that contribute to pipe deterioration,

Figure 1. Study area location on Google Maps.

as well as designing a system capable of assessing and modeling the pipe failure rate. The proposed methodology encompasses several steps commencing from the data collection until achieving the study objective of estimating the failure rate. The overall flow diagram of the research methodology is displayed in Figure 3. It includes four major phases: variables selection, model building, data analytics, and model application.

In the first phase, data on both the main and secondary networks over a period of seven years are collected. Data are divided into two sets; the first set is for building the model and setting its various parameters, and the second set is for model validation and testing its robustness to estimate the output variables. This is followed by identifying the factors (variables) that mostly contribute to the networks' deterioration, as well as selecting the predictor and response variables from El Pedregal's archived data. The predictor variables are specified to be the pipe diameter and thickness, while the response variable is identified as the failure rate.

The second phase involves building and designing the model architecture. Numerous forms of the RA models are defined in this phase. These exemplify the simple linear regression, multiple regression, and polynomial regression. After simulating and analyzing the data, a scatter plot is generated automatically to check the forms

Figure 2. Water networks construction in El Pedregal.

Table 1. Sample of the collected data.

Diameter (inch)	**Thickness (inch) Serie 6.6 (Class15)**	**Thickness (inch) Serie 10 (Class10)**	**Thickness (inch) Serie 13.3 (Class7.5)**	**Thickness (inch) Serie 20 (Class5)**
2.48	0.17	0.12	0.09	0.06
2.95	0.21	0.14	0.11	0.07
3.54	0.25	0.17	0.13	0.09
4.33	0.30	0.21	0.16	0.11
5.51	0.39	0.26	0.20	0.14
6.30	0.44	0.30	0.23	0.16
7.87	0.55	0.38	0.29	0.19
9.84	0.69	0.47	0.36	0.24
12.40	0.87	0.59	0.45	0.30
13.98	0.98	0.67	0.51	0.34
15.75	1.10	0.75	0.57	0.39
17.72	1.24	0.85	0.64	0.43
19.69	1.37	0.94	0.71	0.48

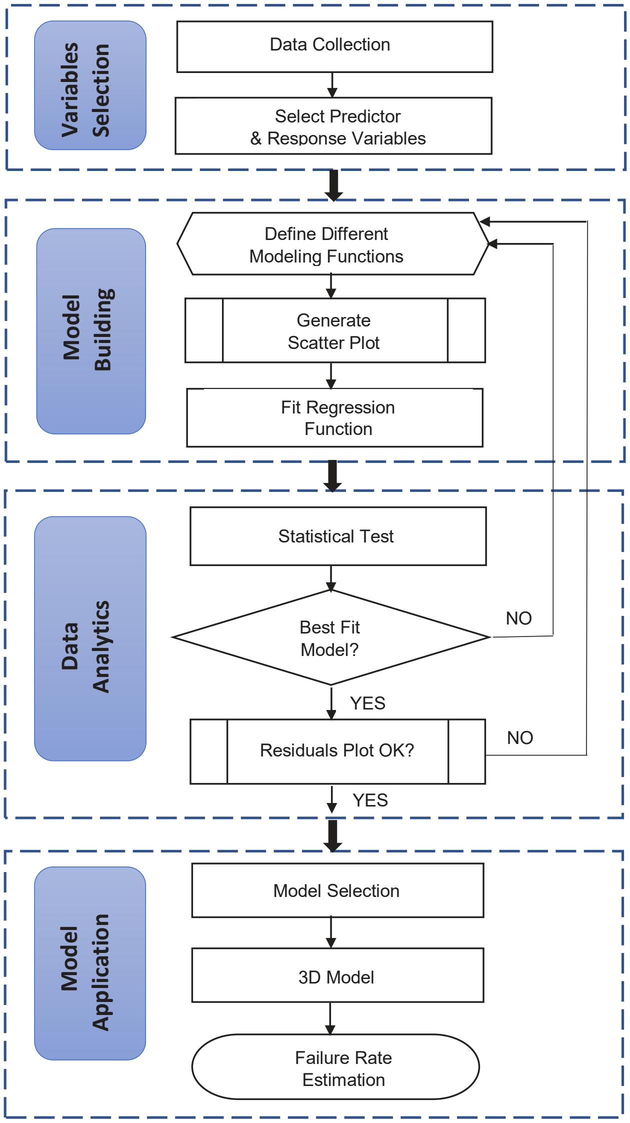

Figure 3. Overall flowchart for pipe failure estimation.

of linearity. This graph also determines the best fit model and provides a prediction of the pipe failure rate. Figure 4 displays the regression model building.

In the data analytics phase, different diagnostic checks are implemented to investigate multiple RA scenarios and interrelated functions of the proposed model. In this concern, the statistical significance of the assessed relationships is computed, which signifies the degree of confidence that the actual relationship is close to the assessed relationship (Elwakil 2017). Hence, the model is tested against four statistical metrics to underscore the goodness of fit and to ensure its robustness. These metrics comprise R-square (R^2), adjusted R-square (Adj R^2), the sum of squares due to error (SSE), and root mean squared error (RMSE). The goodness of fit of the model is determined according to the highest R^2 and Adj R^2, and the least SSE and RMSE. Additional residual graphs are conducted to corroborate the efficacy of the proposed model. In the fourth phase, the model that satisfies the statistical test conditions and the residual analysis is chosen as the best model, which will be applied later for the assessment and modeling of water system failure. Next, a 3D schematic representation was created for the selected model.

Model Development and Results

The previously described phases of the regression model (shown in Figure 3) were implemented in *MATLAB © R2019b* by utilizing

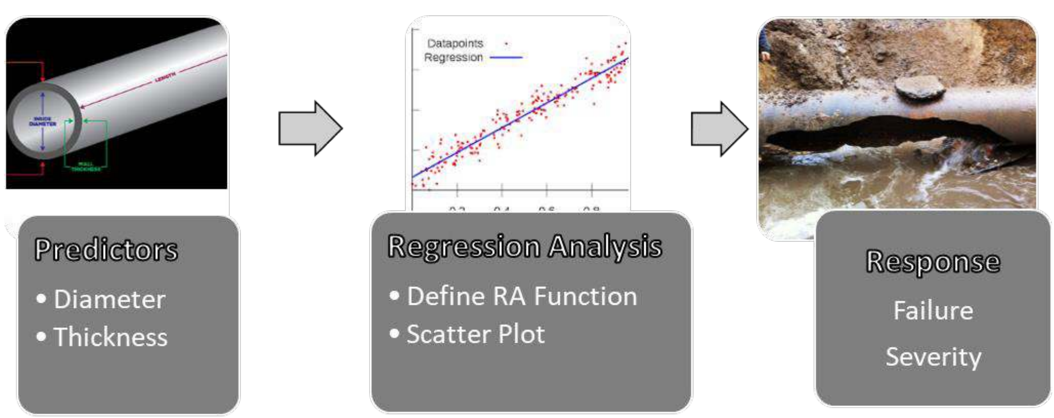

Figure 4. Data fitting using regression analysis.

the regression fitting Toolbox. First, the predictor variables (pipe diameter, thickness) and the response variable (pipe failure) were fed to the RA machine. Subsequent to processing and simulating the introduced data, a scatter plot was produced, then tested for the form of relationship, which indicated a positive linear relationship between the two predictors (diameter, thickness) as shown in Figure 5. However, the statistical analysis results revealed a negative linear relationship between the response variable (failure rate) and each of the predictors.

Since there exist two predictor variables, and after checking the function's pattern, the multiple regression function was employed to fit the data. Different multiple regression models were generated and statistically tested. These tests are conducive to assess the goodness of fit and opting for the best fit model. Several diagnostic criteria were computed and compared, as well as the interactions between a proliferation of parameters, which culminate in choosing the best model. Consequently, the best possible data fitting scenarios were determined in accordance with the highest R^2 and Adj R^2 and the lowest SSE and RMSE. The statistical analysis results reflect that R^2 is 0.9767, Adj R^2 is 0.9745, SSE is 0.0008, and RMSE is 0.0113. Since all four criteria delivered satisfactory results, the best regression model was selected. The mathematical definition of this model is presented in Equation (4):

$$y = -0.069x_1 - 0.048x_2 + 0.032 \tag{4}$$

where, x_1 is the pipe diameter, x_2 is the thickness, and y is the corresponding water pipe failure. In addition, a 3D visualization scheme was extracted for the optimal model, as showcased in Figure 6.

Furthermore, a residual analysis was carried out on the developed model to validate numerous hypotheses related to the model building; such hypotheses encompass homoscedasticity, normality of the error distribution, and lack of correlation. The first hypothesis states that the deviation from the regression line should be the same for all X values, which could be validated by generating the residuals plot of the failure model, as represented in Figure 7. Analyzing this figure demonstrates that approximately all the residuals have tendencies to be constant. Therefore, the outcomes of this hypothesis are deemed reasonable. The normality of the error distribution that specifies departures from normality was conducted. Examining the probability of normal distribution reveals no significant errors or notable outliers. Thus, the proposed model looks sound under this hypothesis. Finally, the lack of correlation measures the independency of error around the regression line. Figure 7 shows that the positive residuals and the negative residuals are symmetrically distributed around zero, which is confirming once again the coherency of the pipe failure model. In cases where the residual analysis does not indicate that the model hypotheses are satisfied, it often proposes solutions in which the model can be modified and rebuilt in order to attain better outcomes.

Conclusions and Future Studies

This paper developed a regression-based model to estimate the level of failure in water supply systems. Following the data collection from the city of El Pedregal in Peru, numerous diagnostic checks were conducted to test the interactions between manifold variables and algorithms. After fitting the

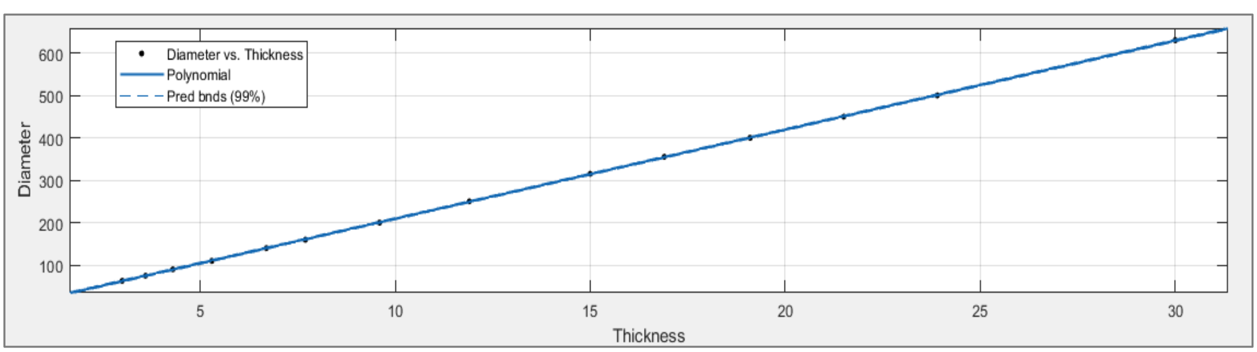

Figure 5. Relationship between diameter and thickness.

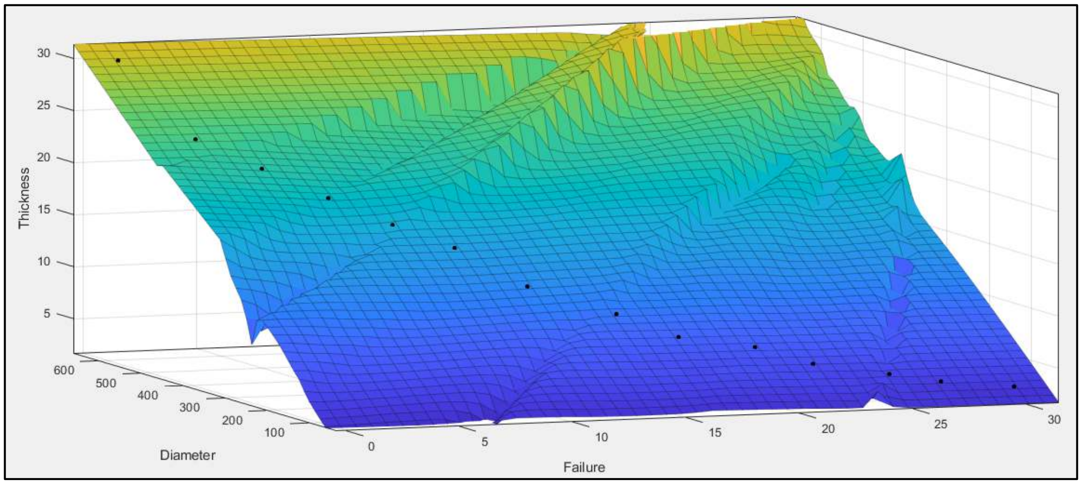

Figure 6. 3D surface presentation. This Figure indicates that the likelihood of water pipe failure increases as the pipe diameter and/or thickness decreases.

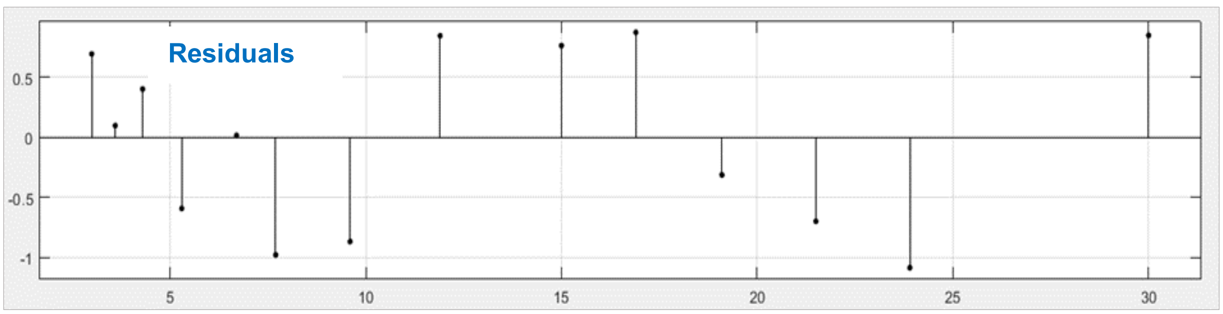

Figure 7. Model's residuals plot.

regression functions and generating a scatter plot, various multiple regression models were produced and statistically tested. The models' performance was compared against several evaluation criteria, which revealed promising results. The optimum model was selected since it achieved the highest R^2 and Adj R^2 of 0.9767 and 0.9745, respectively, and the least SSE and RMSE of 0.0008 and 0.0113, respectively. A 3D visualization plot was created automatically and the model was validated via a residual analysis scheme in which the outcome proved to be satisfactory and sound. Despite the high performance of the proposed method, there exist some limitations, as the model is designed only for PVC pipes; consequently, it cannot model the deterioration or assess the failure rates of other water pipes. This research contributed to the body of knowledge by mathematically modeling the water pipe failure with respect to the pipe diameter and thickness, in addition to creating a 3D visualization representation that can be easily perceived. The 3D surface plot reveals that pipe failure rates in El Pedregal will increase as the diameter and/or thickness decrease. In other words, a water pipe with larger diameter and/or thickness is less prone to failure and more likely to resist breakages.

Some of the suggested future topics may cover the limitations of this research by investigating the deterioration phenomena of other pipe materials, such as cast iron, ductile iron, and asbestos cement. Thus, creating new models that evaluate the level of failure in these pipes. Others may explore the automated monitoring systems using Smart Pipes, Intelligent Pigs, and Robotics for a more coherent condition assessment of the water system. Other research can investigate the Augmented Reality approach that offers a human-computer interface for real-time visualization of anomalies and defects in water pipelines. Moreover, an integrated predictive model could be accomplished by fusing and linking data streams from multiple remote sensing technologies and sensors, such as the Ground Penetrating Radar (GPR), radiographic methods, and infrared sensors that can detect the pipe deterioration and locate its leakage in a nondestructive way. This predictive model can be merged with GIS to generate highly accurate maps, hence allowing a de facto visualization of the network risk of failure. These applications could reasonably minimize the disruptions to roads and businesses, as well as, reduce the cost and time incurred.

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References

American Society of Civil Engineers (ASCE). 2017. *Infrastructure Report Card*. Available at: https://www.infrastructurereportcard.org/cat-item/drinking_water/. Accessed August 28, 2020.

American Water Works Association (AWWA). 2012. *Buried No Longer: Confronting Americas Water Infrastructure Challenge*. Available at: http://www.climateneeds.umd.edu/reports/American-Water-Works.pdf. Accessed August 28, 2020.

Asnaashari, A., E.A. McBean, I. Shahrour, and B. Gharabaghi. 2009. Prediction of watermain failure frequencies using multiple and Poisson regression. *Water Supply* 9(1): 9-19. Available at: https://doi.org/10.2166/ws.2009.020. Accessed August 28, 2020.

Aydogdu, M. and M. Firat. 2015. Estimation of failure rate in water distribution network using fuzzy clustering and LS-SVM methods. *Water Resources Management* 29: 1575-1590. Available at: https://doi.org/10.1007/s11269-014-0895-5. Accessed August 28, 2020.

Barlow, M. and T. Clarke. 2007. *The Struggle for Latin America's Water*. Nacla Reporting on the America's Since 1967. Available at: https://nacla.org/article/struggle-latin-america%27s-water. Accessed August 28, 2020.

Chatterjee, S. and A.S. Hadi. 2012. *Regression Analysis by Example*. 5th Edition. John Wiley & Sons, Inc., New Jersey, USA.

Christodoulou, S., A. Agathokleous, B. Charalambous, and A. Adamou. 2010. Proactive risk-based integrity assessment of water distribution networks. *Water Resources Management* 24: 3715-3730. DOI: 10.1007/s11269-010-9629-5.

Constantine, A., J. Darroch, and R. Miller. 1996. Predicting underground pipe failure. *Water* 23(2): 9-10. Available at: http://hdl.handle.net/102.100.100/229501?index=1. Accessed August 28, 2020.

Dawood, T., E. Elwakil, H.M. Novoa, and J.F.G. Delgado. 2019a. Water pipe failure prediction and risk models: State-of-the-art review. *Canadian Journal of Civil Engineering*. In press. Available at: http://dx.doi.org/10.1139/cjce-2019-0481. Accessed August 28, 2020.

Dawood, T., E. Elwakil, H.M. Novoa, and J.F.G. Delgado. 2019b. A contamination risk model for water distribution networks. In: *Proceedings of the International Conference on Engineering, Science and Technology*. October 7-10, 2019, Denver, CO, USA. Available at: https://www.2019.iconest.net/fulltext/pdf/IConEST037.pdf. Accessed August 28, 2020.

Deb, A.K., Y. Hasit, J.F.M. Grablutz, and R.K. Herz. 1998. Quantifying future rehabilitation and replacement needs of water mains. *AWWA Research Foundation*. Denver, CO, USA.

Dridi, L., A. Mailhot, M. Parizeau, and J.P. Villeneuve. 2009. Multiobjective approach for pipe replacement based on Bayesian inference of break model parameters. *Journal of Water Resources Planning and Management* 135(5): 344-354. Available at: https://doi.org/10.1061/(ASCE)0733-9496(2009)135:5(344). Accessed August 28, 2020.

Elwakil, E. 2017. Integrating analytical hierarchy process and regression for assessing construction organizations' performance. *International Journal of Construction Management* 17(1): 76-88. Available at: https://doi.org/10.1080/15623599.2016.1187247. Accessed August 28, 2020.

Fahmy, M. and O. Moselhi. 2009. Forecasting the remaining useful life of cast iron water mains. *Journal of Performance Constructed Facilities* 23(4): 269-275. Available at: https://doi.org/10.1061/(ASCE)0887-3828(2009)23:4(269). Accessed August 28, 2020.

Fayaz, M., I. Ullah, and D.-H. Kim. 2018. Underground risk index assessment and prediction using a simplified hierarchical fuzzy logic model and Kalman filter. *Processes* 6(8): 103. DOI: 10.3390/pr6080103.

Folkman, S. 2018. *Water Main Break Rates in the USA and Canada: A Comprehensive Study*. *Mechanical and Aerospace Engineering Faculty Publications*. Paper 174. Available at: https://digitalcommons.usu.edu/mae_facpub/174/. Accessed August 28, 2020.

Harvey, R., E.A. McBean, and B. Gharabaghi. 2014. Predicting the timing of water main failure using artificial neural networks. *Journal of Water Resources Planning and Management* 140(4): 425-434. Available at: https://doi.org/10.1061/(ASCE)WR.1943-5452.0000354. Accessed August 28, 2020.

Jacobs, P. and B. Karney. 1994. GIS development with application to cast iron water main breakage rate. *2nd International Conference on Water Pipeline Systems*. Edinburgh, Scotland.

Jeffrey, L.A. 1985. Predicting urban water distribution maintenance strategies: A case study of New Haven. M.Sc. Thesis, Massachusetts Institute of Technology, Cambridge, MA, USA.

Kleiner, Y. and B. Rajani. 2001a. Comprehensive review of structural deterioration of water mains: Statistical models. *Urban Water* 3(3): 131-150. DOI: 10.1016/S1462-0758(01)00033-4.

Kleiner, Y. and B. Rajani. 2001b. Comprehensive review of structural deterioration of water mains: Physically based models. *Urban Water* 3(3): 151-164. DOI: 10.1016/S1462-0758(01)00032-2.

Kutner, M., C. Nachtsheim, and J. Neter. 2003. *Applied Linear Regression Models*. 4th Edition. McGraw-Hill Company Inc., New York, USA.

Kutner, M., C. Nachtsheim, J. Neter, and W. Li. 2005. *Applied Linear Statistical Models*. 5th Edition. McGraw-Hill Company Inc., New York, USA.

Li, D., and W. Yao. 2016. Risk assessment of long-distance water transmission pipeline based on fuzzy similarity evaluation approach. *12th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (ICNC-FSKD)*. Changsha, China. Available at: https://ieeexplore.ieee.org/abstract/document/7603331. Accessed August 28, 2020.

Malinowska, A.A. 2017. Fuzzy inference-based approach to the mining-induced pipeline failure estimation. *Natural Hazards* 85: 621-636. DOI: 10.1007/s11069-016-2594-4.

Mavin, K. 1996. *Predicting the Failure Performance of Individual Water Mains*. Urban Water Research Association of Australia, Research Report No. 114, Melbourne, Australia.

McMullen, L.D. 1982. Advanced concepts in soil evaluation for exterior pipeline corrosion. *Proceeding of the AWWA Annual Conference*. Miami, FL, USA.

Najjaran, H., B. Rajani, and R. Sadiq. 2004. A fuzzy expert system for deterioration modeling of buried metallic pipes. *IEEE Annual Meeting of the Fuzzy Information*. Banff, Alberta, Canada, June 27-30, 2004, pp. 1-6.

Sattar, A.M.A., Ö.F. Ertuğrul, B. Gharabaghi, E.A. McBean, and J. Cao. 2019. Extreme learning machine model for water network management. *Neural Computing and Applications* 31(1): 157-169. DOI: 10.1007/s00521-017-2987-7.

Shamir, U. and C. Howard. 1979. An analytic approach to scheduling pipe replacement. *Journal of American Water Works Association* 71(5): 248-258. Available at: https://doi.org/10.1002/j.1551-8833.1979.tb04345.x. Accessed August 28, 2020.

St. Clair, A.M. and S. Sinha. 2012. State-of-the-technology review on water pipe condition, deterioration and failure rate prediction models! *Urban Water Journal* 9(2): 85-112. Available at: https://doi.org/10.1080/1573062X.2011.644566. Accessed August 28, 2020.

Stensrud, A.B. 2016. Dreams of growth and fear of water crisis: The ambivalence of "progress" in the Majes-Siguas Irrigation Project, Peru. *History and Anthropology* 27(5): 569-584. Available at: https://doi.org/10.1080/02757206.2016.1222526. Accessed August 28, 2020.

Tabesh, M., J. Soltani, R. Farmani, and D. Savic. 2009. Assessing pipe failure rate and mechanical reliability of water distribution networks using data-driven modeling. *Journal of Hydroinformatics* 11(1): 1-17. Available at: https://doi.org/10.2166/hydro.2009.008. Accessed August 28, 2020.

Walski, T. and A. Pelliccia. 1982. Economic analysis of water main breaks. *Journal of American Water Works Association* 74(3): 140-147. Available at: https://doi.org/10.1002/j.1551-8833.1982.tb04874.x. Accessed August 28, 2020.

Wang, Y., T. Zayed, and O. Moselhi. 2009. Prediction models for annual break rates of water mains. *Journal of Performance of Constructed Facilities* 23(1): 47-54. Available at: https://doi.org/10.1061/(ASCE)0887-3828(2009)23:1(47). Accessed August 28, 2020.

Winkler, D., M. Haltmeier, M. Kleidorfer, W. Rauch, and F. Tscheikner-Gratl. 2018. Pipe failure modelling for water distribution networks using boosted decision trees. *Structure and Infrastructure Engineering* 14(10): 1402-1411. DOI: 10.1080/15732479.2018.1443145.

The World Bank. 2018. National Urban Cadaster and Municipal Support Project (P162278). Available at: http://documents1.worldbank.org/curated/en/115551541449971634/pdf/Concept-Project-Information-Document-Integrated-Safeguards-Data-Sheet-National-Urban-Cadaster-and-Municipal-Support-Project-P162278.pdf. Accessed August 28, 2020.