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PREDICTING CAPACITY OF DEFECTED PIPE UNDER BENDING MOMENT WITH DATA-DRIVEN MODEL

Hieu C. Phan[1], Nang D. Bui[2], Tiep D. Pham[3], Huan T. Duong[4]

[1] Le Quy Don Technical University, 236 Hoang Quoc Viet, Hanoi, Vietnam.
e-mail: phanchihieu@lqdtu.edu.vn
[2] Le Quy Don Technical University, 236 Hoang Quoc Viet, Hanoi, Vietnam.
e-mail: ducnangbui@lqdtu.edu.vn
[3] Le Quy Don Technical University, 236 Hoang Quoc Viet, Hanoi, Vietnam.
e-mail: phamductiep@lqdtu.edu.vn
[4] Vietnam National University of Agriculture, Trau Quy, Gia Lam, Hanoi, Vietnam.
e-mail: dthuan@vnua.edu.vn

ABSTRACT

Water mains which suffered from corrosive environment and various loads/effects. This leads to the simultaneous occurrence of the decrease of the pipe capacity and the appearance of significant bending moments within the pipe. Various investigation in literature focused on the stress of defected pipe due to burst pressure for oil and gas pipe under the high internal pressure, rather than the bended water mains. Primitive studies on this problem are at the observation step without providing an applicable model for practice. Since finding analytical solution for corrosion pipe is a challenging task because of the localized of the defects, the Finite Element Analysis (FEA) is an effective alternative. The critical drawback of FEA is that the problem needs to analysis separately with computational expense and required highly skilled experts. To ease these difficulties, a data-driven model is developed based on the database generated from FEAs and labeled by their results. The application of machine learning techniques improves the accuracy of the conventionally statistical regression models such as linear regression due to the flexible of the model and thus a trained data-driven model is a practical approach to solve the problem.

Key words: *Defected pipe, computational intelligence, machine learning, finite element analysis.*

1. INTRODUCTION

Water mains are vital systems for human communities, however, these networks normally suffered from corrosive environment of surrounding soil and various loads/effects such as land sliding, non-uniform supports or temperature changing etc. Unlike pipeline used for transporting oil and gas which design mainly for internal pressure and a significant temperature change due to the difference between transported medium and environment [32], unexpected bending moment can be the major factor of failure for water main. Statistics in [12] shows that the critical failure mode of water mains dues to circular crack accounting for up to 56 percent of failure event in North America compared to this of 8 percent for longitudinal crack. This implies the most critical thread to water mains is the bending moment or the axial force (corresponding to circular crack) rather than ring bending or internal pressure (corresponding to longitudinal crack). The bending moments may derive from various sources such as land sliding [27, 33], ununiform supports [2, 20], frost-induced ground deformations [34], strike-slip faults [36] etc.

Along with circular crack, corrosion is another major threat to water mains with 28 percent of failures comes from such source of degradation [12] and the situation can be worse with the combination of such failure modes. Makar et al. [22] have conducted experiments and reported the closely relationship of corrosion and appearance of circular crack. The combination of defected pipe under bending moment thus has been gaining interest of researchers [31], [20], [19], [25], [38]. Roy et al. [31] have validated the FEA and experiment results of pipe under bending, axial load, internal pressure and temperature change. Liyanage and Dhar [20] investigated the defected pipe placed on springs and voids represented for soil support and erosion due to water leak, respectively. In a report of Liu et al. [19], the failure loci are provided with both experiment and Finite Element Analysis (FEA) simulation provides the insight behavior of pipelines with corrosion under combining loads. Mondal and Dhar in [25] have validated the results in [19] with discussion on its failure criteria and investigate the reduction of pipe internal pressure under the combination of loads (i.e. with bending and axial loads).

Many attempts to modelized the capacity of defected pipe under bending moment are made and can be found in [1, 7, 8, 37, 38] with most of the study using FEA to obtain the failure moment. The requirement of simulation structure with FEA may lead to a cumbersome work with requirement expert level and computational cost. Besides, the nonlinear relationship of the inputs to the output variable(s) cannot be provided without repetition of FEA. In the case of combining structure capacity prediction with other algorithm (e.g. optimization or simulation-related reliability assessment), this drawback of the FEA approach surges and can be a critical problem for successfully finish such cumbersome work. Consequently, the data-driven models commonly applied based on the database generated from FEA or experiment as in [29] or [11].

In this study, results of 208 FEA simulations are composed to be a database for a machine learning model, the Random Forest Regression (RFR). The following sections are organized such that: the second section discusses on the establish of a proper FE model, the third one presented the fundamental of the chosen data-driven model, the RFR. Discussion on the database and developed model for predicting pipe bending capacity will be in the fourth section and finally, conclusion of contribution and future works are at the last section.

2. FINITE ELEMENT MODEL

The FEA in this study is implemented on the Abaqus software which has the ability of simulating nonlinear behavior of the structure in the post-yielding state. A quarter pipe model with the defected on the top/crown and the symmetric constrains are applied as in Fig.1. The x-symmetric and z-symmetric constrains are set along the longitudinal circular cuts of the pipe, respectively, to reduce the elements in the models and thus reduce the computation cost. The defection dimension including the depth, d; length, l; and width, w_{arc}, of the defect with sharp edge. Comparison between the difference of the sharp and smooth edges has been conducted in [6] with minor difference. However, the smooth edge required much more computational effort, and thus, the sharp edge is used. The beam-style Multiple Point Constrain, MPC, is used with the reference point located at the other end of the model. The bending moment on the model is applied on this reference point.

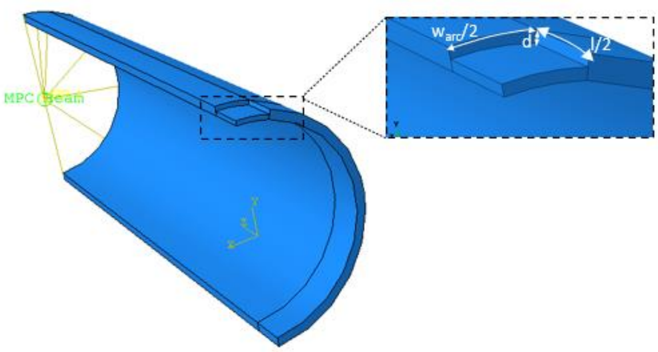

Figure 1. Quarter model of defected pipe on Abaqus

Various material models are proposed as summarized in [6] and illustrated in Fig.2. The non-linear true stress-strain curves based on experiment is ideal for exact simulation. However, the drawback is the increase of inputs for data-driven model break such curve into points or mathematically modelized them. The bilinear and elastic-perfectly plastic are preferable to present for the behavior of material due to the simplification and the bilinear model is chosen in this study to develop the database. Properties of material thus require the stress and strain of the yield and ultimate points including: yield strength, σ_y, ultimate strength, σ_u, and their corresponding strain, ε_y and ε_u. These parameters of metal material are collected from literature [10, 19, 21, 23, 28] and summarized in Table I.

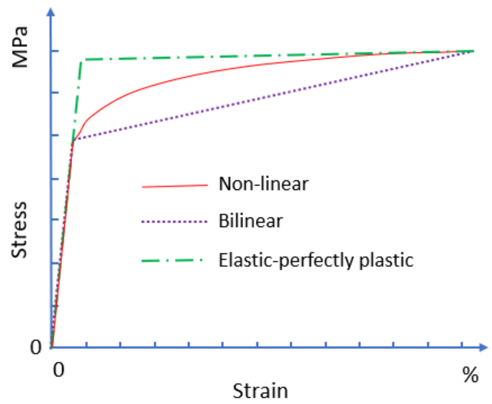

Figure 2. Different material models [6]

Table I. Collected material properties

Material	σ_y (MPa)	σ_u (MPa)	ε_y -	ε_u -	Reference
Cast Iron	161.9	218.64	0.0031	0.0067	[23]
Steel, X42	290	415	0.0014	0.1036	[19]
Steel, X60_1	452	542	0.0021	0.043	[10]
Steel, X60_2	414	600	0.0020	0.095	[10]
Steel, X65	464.5	563.8	0.0022	0.061	[28]
Steel, X70_1	508	667	0.0024	0.095	[21]
Steel, X70_2	523	701	0.0025	0.095	[21]
Steel, X80	524	685	0.0025	0.078	[21]

Various failure criteria are also used for defining the failure state of the pipe ([19], [18] and [25]). Liu et al. in [19] has defined that a pipe is considered to be failure if:

(1) *"The average von Mises equivalent stress across the full remaining thickness reaches the true ultimate tensile strength of the pipe material; or the von Mises equivalent stress at diametrically opposite from the corrosion defect reaches the yield strength of the pipe material; or the onset of local collapse or global instability/buckling*."

However, the early failure of the pipe where the yield stress at the opposite point of the defect appear. The structures are considered to be failure due to the exceed of yield stress [25]. This leads to the over conservative prediction of pipe capacity. Consequently, [25] use the failure criteria as in [18] with the definition of pipe failure is:

(2) *"The average von Mises equivalent stress throughout the thickness reaches the true ultimate strength of the pipe material"*.

This study adjusts the failure criteria (2), the failure criteria to decide the ultimate bending capacity of pipe, M, is equal to the quantity of moment applied on pipe where:

(3) **"*Failure occurred if any point in the structure reaches the ultimate stress*"**.

Fig.3 illustrates the difference of material models and failure criteria are provided with the observation at the failure point in the ligament of the pipe. The control case is conducted with the inputs are: D=203.2mm, t=82mm, d=4.1, l=65.6mm, w_{arc}=65.6mm, σ_y=290MPa, σ_u=415MPa, ε_y=0.0014, ε_u=0.1036 (steel, X42). The intact pipe capacity calculated based on classic theory is 109 kNm [25]. The moment capacity of pipe with the true/actual, bilinear and Elastic-perfectly plastic stress-stress curves (M_{c_Tr}, M_{c_Bi}, M_{c_Ep}) are: 67, 93 and 98kNm. Compared to the result in [25], M_{c_Tr} in this study is almost equal (~98kNm versus 97kNm, respectively) and provide a validation for the present FEA model. Analogously, the M_{c_Ep}, in this study compared to Liu et al. with failure criteria (1) have minor difference (67kNm versus ~68kNm, respectively). The simulated M_{c_Bi} with failure criteria (3) is within the range set by [M_{c_Ep}, M_{c_Tr}] or it is higher than M_{c_Ep} and less than M_{c_Tr}.

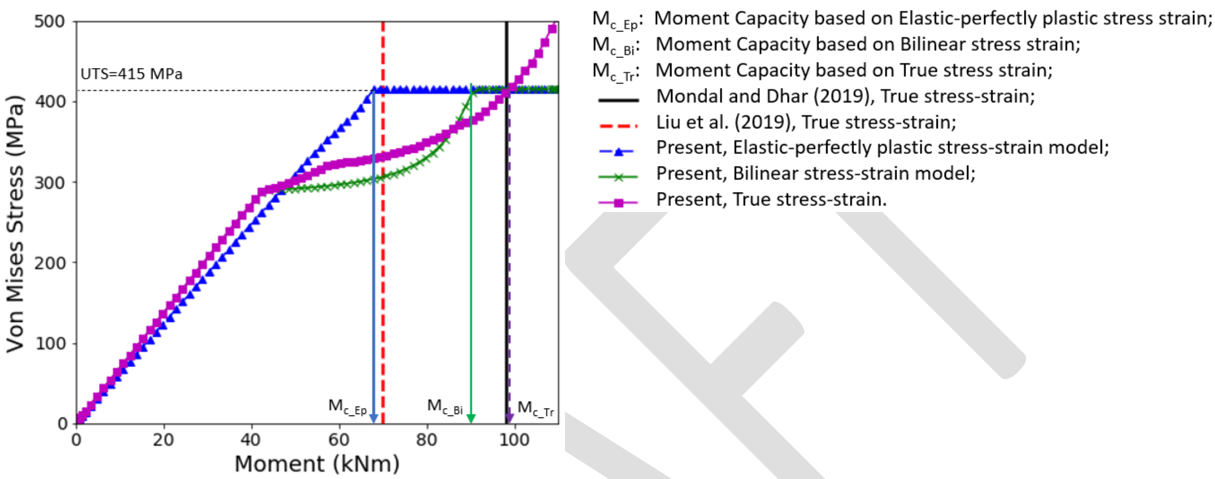

Figure 3. Comparative results at the failure point

3. DEVELOPING A DATA-DRIVEN MODEL WITH RANDOM FOREST REGRESSION

Unlike conventional mechanical models, data-driven model does not attempt to establishing and solving mechanical equilibrium equations. They rely heavily on a database labeled by the interested variable for each set of input. A learning process is conducted with the target to minimize the error between predicted and label or “actual” values. Once the model is developed, the effect of an input to the output is established. This process is fostered by the computer power and the redundancy of data available [26]. Technically, the database is splitted into train and test set for training and validating processes, respectively. The test set, as its name, used to test the performance of the developed model on the data that it has never “seen” or not appeared in the train set [14].

Various algorithms have been developed and can be used for developing a data-driven model. Some of them are: Artificial Neural Network, ANN (introduce by McCulloch and Pitts [24] and developed by many studies such as [17] [5], [15], [30]); Support vector machine, SVM ([3], [9], [35]); Random Forest, RF; Extreme Gradient Boosting (XGBoost) [13]; Adaptive neuro fuzzy inference system (ANFIS) [16] etc. In this study, primary trials on ANN, SVM and RF to develop the data-driven model based on samples generated from FEA. With this specific database which contains 200 samples, RF provides the best performance on the test set and thus chosen.

Random Forest (RF or Random Forest Regression, RFR) is an ensemble of the decision trees. Each tree in the forest established by the Classification And Regression Tree, CART, algorithm [4] with a random part of the database or a sub-database randomly selected. The CART algorithm minimizes the loss function which can be Entropy, Gini or errors of the tree [14] and the Mean Squared Error, MSE, is chosen in this study. The decision tree is repeatedly established to create a number of trees or a forest and a voting process is conducted to aggregate the final prediction.

4. FEA DATABASE AND THE DEVELOPED MODEL

A wide range of materials and pipe dimension are used with different defects sizes are chosen as the generated input for the FEA. Pipe and defect dimension inputs are outer diameter, D, wall thickness, t, of pipe and depth, d, length, l, and width, w_{arc}, of defect. Because the bilinear material model is applied, inputs related to material properties include yield strength, σ_y, ultimate strength, σ_u, and their corresponding strain, ε_y and ε_u. The Abaqus Python script is applied to obtain a semi-automatic model generation of the database. This accelerate the data generating process and partly reduce the cumbersome work where a large number of simulations involved. Table II provides the list of inputs and some selected samples in the database.

Table II. Selective FEA database

	D (mm)	t (mm)	d (mm)	l (mm)	w_{arc} (mm)	σ_y (MPa)	σ_u (MPa)	ε_y -	ε_u -	M (kNm)
1	762	17.5	0	0	0	290	415	0.001376	0.1036	3860
2	762	17.5	0	0	0	452	542	0.002145	0.043	5040
3	762	17.5	0	0	0	414	600	0.001965	0.095	5430
…	…	…	…	…	…	…	…	…	…	…
206	914	25.4	0.5	100	50.05	464.5	563.8	0.002205	0.061	10800
207	914	25.4	0.5	100	50.05	523	701	0.002482	0.095	12000
208	914	25.4	0.5	100	50.05	524	685	0.002487	0.078	11880

Basic descriptive statistics of the generated database are given in Table III providing the mean, standard deviation, maximum and minimum values of each input. As mentioned in our previous study [11], the maximum and minimum value of each input in the database can be set as the boundaries for a valid prediction. The mean and standard deviation of bending moment capacity, M, in the database are 3566 and 4066 kNm, respectively. The minimum and maximum values of this variable are 45.4 kNm and 13580 kNm which established a wide range of possible pipe moment capacity.

Table III. Descriptive statistics of the FEA database

	D (mm)	t (mm)	d (mm)	l (mm)	w_{arc} (mm)	σ_y (MPa)	σ_u (MPa)	ε_y -	ε_u -	M (kNm)
mean	622.234	13.028	5.025	72.946	134.022	436.674	570.386	0.002117	0.090100	3566.439
std	338.915	5.837	4.025	93.367	164.046	85.050	103.314	0.000385	0.159162	4066.432
min	180.000	5.560	0.000	0.000	0.000	161.900	218.640	0.001376	0.006739	45.400
max	1219.000	25.400	14.000	500.000	718.168	524.000	701.000	0.003085	2.103600	13580.000

Further observation on the database is illustrated in Fig.4 which presents the matrix of coefficients of correlation among input and output variables. In this figure, area of each square is equivalent to the Pearson correlation coefficient of variable in the horizontal and vertical axis. It is predictable that squares along the diagonal of this matrix are the largest indicating the self-correlation value at 1.0. The most significant relationships are the correlation of pipe diameter and wall thickness to the capacity of pipe. The dimensions of defect have less significant level. The depth, length and width of the defect have correlation coefficients with the descending order. It is predictable to observe the strong effect of d to the capacity of pipe. Also, the strong relationship between stress and strain of the material can be predictable. However, the stronger influence of defect length to defect wide is remarkable which indicate the more important level of l to w_{arc}.

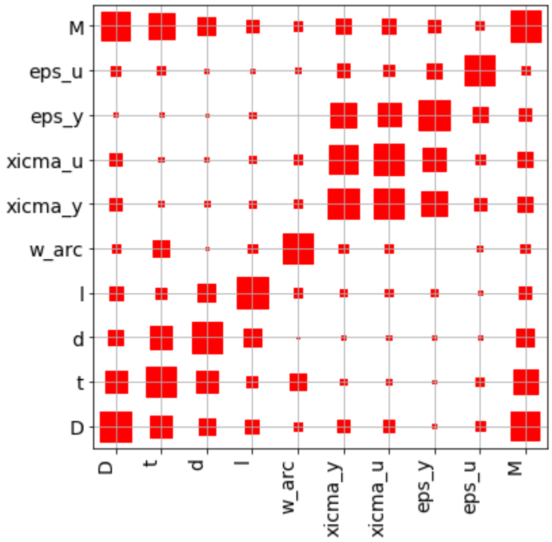

Figure 4. Correlation coefficient matrix among variables (larger squares implie larger value of coefficients)

As earlier discussion, the database generated by Abaqus FEA and labeled with moment capacity of defected pipe is used to develop the RFR model. The database is splitted with the 0.8/0.2 ratio for train set and test set respectively. With 160-sample train set, the model is developed and then such model is validated with the 40-sample test set. Table IV provides the evaluation metrics on both train and test set of the model after training process. The coefficient of determination, R^2, on both sub-databases are consistently higher than 0.99 indicating a well-matched of the model and the actual trend of the output. The Mean Absolute Error, MAE, at 66.93 kNm on train set and higher at 165.65 kNm on test set are minor compared to the mean value of (e.g. 3566.44 kNm) as in Table II. The Mean Absolute Percentage Error, MAPE, reinforced this evaluation with quantity of this type of error are all less than 5 percent (0.021 on train set and 0.0486 on test set). The means of error between predicted and actual value of M are also closed to zero indicating a non-bias prediction along with the acceptable standard deviation of such error. Fig.5 illustrates the evaluation process visually with the closely following of the datapoints to the 1:1 line of the predicted and simulated axis. This implies that the trend (direction of the datapoints) of the model is satisfied and error (distance between datapoints and the 1:1 line) of such model are minor.

Table IV. Evaluation metrics of the RFR model on train and test set

	Unit	Train set	Test set
R^2	-	0.9991	0.9930
MAE	(kNm)	66.9364	165.6581
MAPE	-	0.0210	0.0486
mean error	(kNm)	6.1003	-40.0941
std error	-	125.2573	291.1223

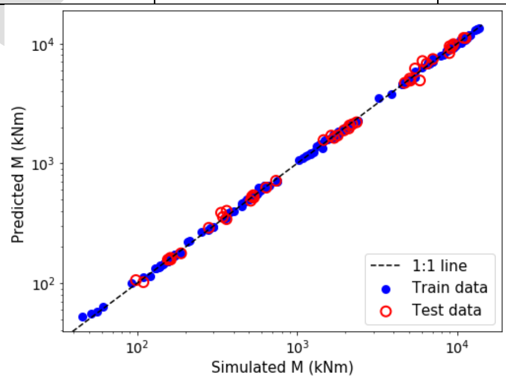

Figure 5. Predicted versus simulated (FEA) of pipe moment capacity

The feature importance for each input, which found by the average depth of each input appeared in decision trees [26], are showed in Fig.6 with the firstly ranked position belongs to pipe diameter, D at 0.9. This is well-matched with the correlation matrix in Fig.4. The other significant inputs are the wall thickness and the ultimate strength of material at 0.04 and 0.02, respectively. Unlike the relative positions obtained in Fig.4, length of defect is the most important variable among defect dimension inputs. Meanwhile, the depth of the defect, d, conquered this position in Fig.4. The strains of material are the most insignificant variables compared to other inputs with the important levels are less than 0.01

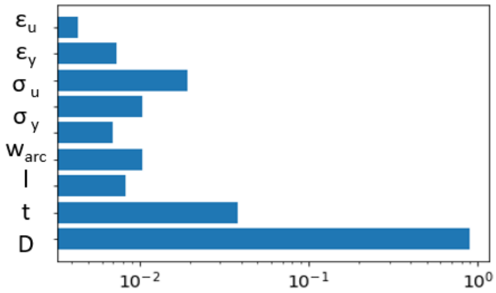

Figure 6. Feature importance of input variables

5. CONCLUSION

This study has implemented an extensive simulation-based database for the defected pipe under the bending force which are commonly appeared in buried pipe as a major cause of failure. A validation is conducted to investigate the validation of the FEA model of this study. Besides, a brief comparison difference between material models, failure criteria are provided for observation. The chosen failure criteria (3) is observed to be between values of criteria (2) and criteria (1). Consequently, FEA models are repeatedly established based on bilinear material models with the incorporation between Abaqus and Python scripts to reduce the cumbersome work of data generating. A set of 208 labeled samples have been generated by FEA. The statistics analysis on this database provides the preliminary evaluation of input important levels. A RFR model then has been developed with appropriate performances such as R^2 and MAPE are 0.993 and 0.0486, respectively. Further development where machine learning model combined with other advance techniques is promising with such high-quality model or the expansion of boundaries for the data-driven model can be conducted.

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