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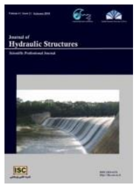

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Application of Artificial Neural Networks for Seismic Analysis and Design of Buried Pipelines in Heterogeneous Soils

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Abstract

Every year, the phenomenon of earthquake causes a lot of human, financial and environmental losses. Transmission pipelines are one of the vital arteries that are very important, however, in the event of an earthquake can cause devastating damages. Safeguarding urban and interurban facilities, including electricity, water supply, oil and gas transmission lines, against these loads requires careful studies and engineering designs. Given that traditional methods for seismic design of pipelines such as FEM modeling and experimental methods are so expensive, a new combined method for predicting the strain of pipes based on the Artificial Neural Network (ANN) is proposed. For this purpose, the parameters of the pipeline including pipe and soil type, length, discharge, path slope, depth, etc. and earthquake-induced characteristics including earthquake acceleration, earthquake occurrence time, Peak ground acceleration (PGA), etc. were included in the model. Earthquake input parameters were considered as input parameters and pipe strains and stresses were considered as output parameter. ANSYS finite element software has also been used to simulate the pipeline and produce training data. The results of finite element software were used as input and output parameters for training and validating artificial neural network. 753 models created using ANSYS and its input/output data divided into three parts to creat ANN model. 70% of the total data were used for training, 15% for validating and 15% for testing the ANN model. Results show that the proposed Method provides a very good agreement with the computational results of the ANSYS with accuracy of 96 percent.

Keywords: Pipeline, Seismic design, Heterogeneous Soil, FEM, ANN

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1. Introduction

Earthquake is one of the natural disasters that causes a lot of human, financial and environmental damages every year. Iran is very vulnerable to earthquakes due to its location on the earthquake belt. Transmission pipelines as one of the vital arteries are very important and especially during natural disasters. Damage to these lines can lead to the spread of hazardous materials which itself can produce further damages. Therefore, the occurrence of earthquakes and its

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consequences has always been one of the concerns of people and officials of countries, especially earthquake-prone countries such as Iran.

Numerical and experimental methods to determine the damage caused by earthquakes in the pipeline require high costs. This cost includes buying expensive FEM software packages or building experimental seismic testing equipment and the wage of professional engineers. Therefore, in this study, artificial neural network is used instead of classical methods in order to achieve the desired results for determining pipe failure. Pipeline response due to wave propagation is usually expressed in terms of the strain of the longitudinal axes of the pipes. The bending strains of pipes are ignored due to the curvature of the earth because they are usually very small [15]. Each earthquake usually includes volumetric waves and surface waves. Volumetric waves weaken rapidly compared to the surface waves as the distance increases. Structures located on the ground are far more vulnerable to earthquakes than underground structures. However, pipelines buried at very shallow depths may be harmed by earthquakes. Therefore, burial depth is an important design parameter in underground pipe lines. In other words, the greater the depth of pipe installation, the lower the levels of earth vibration design can be.

In order to design of buried pipelines using finite element method and to simulate their behavior, the stress and strain created in the pipe due to different loads are calculated and compared with the allowable stress and strain. Then the possibility of application of the pipeline for operation purposes was investigated. Some of the previous studies in this area are mentioned below.

Farhidzadeh et al. (2014) examined the assessment of earthquake damage to reconstruction pipes using acoustic technology at the site using sound waves, construction, and building materials. They state that pipeline coating technology has received considerable attention over the last three decades to extend the operating life of existing underground pipelines without the hassle of excavation, replacement, and laborious embankment. In this paper, the results of an experimental study with the aim of monitoring the performance of full-scale piping systems, subject to static and dynamic (seismic) loading using acoustic diffusion (AE) technique is presented. In particular, two damage mechanisms have been investigated - laminating between the pipeline and the liner, and the initial failure of the liner and a statistical pattern recognition method based on multivariate metamorphic analysis to automatically detect the onset of critical damage. Such a system can inform decision-makers about the need for repairs and ultimately ensure the safe and secure operation of underground infrastructure. [6]

Bavanpour et al. (2011) studied the dangers of earthquake liquefaction of pipelines and the stability of transmission pipes (vital arteries) in a numerical study [2].

Fruits et al. (2010) conducted a seismic evaluation of buried pipelines under permanent deformation of the earth, including liquefaction and landslides, the most effective parameter of which is Permanent Ground Deformation (PGD). Their investigations have been performed on continuous and discontinuous pipes. Their investigation was successfully carried out on a sample of a buried oil pipeline that had failed due to an external corrosion. There were two mechanisms of corrosion of iron oxide and the other was iron sulfide. In addition, it has been proven that the direction of the pipe rupture and failure of the pipeline is due to subsidence, which is consistent with the reported evidence [4].

Bargi et al. (2012) by analyzing the risk of vital arteries using a valid regulation in the world and also the implementation of various finite element models to adapt them to the conditions in Iran have provided models and fragility curves suitable for use in the country [1]

Hosseini et al. (2011) Examined the two factors of pipe health and system flexibility for the reliability of the water pipeline system after the earthquake. The results showed that by strengthening the pipes or replacing the pipes with higher efficiency and the second case is achieved by building a flexible network system. Is realized. On the other hand, values of rotation above 0.005 rad cause many connections to be in the nonlinear range. [3]

Kimishima et al. (2011) Have integrated and investigated the spatial distribution of damage to pipes buried by the Japan Niigata earthquake by the Geographic Information System (GIS). The results show that damage to low pressure gas pipes is often seen near water distribution pipes. Therefore, it is expected that the interaction between the functional losses of installation systems in the post-earthquake repair process in urban areas will be considered. [13]

Meimei Liu et al. (2014) investigated the effect of falling buried gas pipeline objects using finite element numerical method. The results showed that with increasing the relative stiffness of the pipeline-soil, the maximum stress of the pipeline decreased. The penetration depth, however, was independent of the relative hardness of the soil-pipeline. The pipe stress decreases with increasing buried depth and stabilizes when the buried depth is more than 3 m. In this study, a new method to improve the accuracy of the proposed formula for calculating the impact load and penetration depth is presented [7].

Do Hyung Lee et al. (2009) used the relative axial displacement and transverse displacement (crossover) on the buried gas pipeline under multiple earthquakes with different time intervals to obtain its value on the sections of buried pipelines. And introduce the results as a guide for the seismic design of buried gas lines. [10]

The following are some previous studies on the use of artificial neural networks in pipeline design.

Janalizadeh et al. (2014) Investigated the modeling and optimization of the trench layer around the pipeline using artificial neural networks and particle swarm optimization algorithm. In this study, artificial neural networks (ANNs) are used to find the optimal positions of the trench layer around a pipeline and PSO is used to find the best location of the trench layer. The results show that there is a linear relationship between the pipeline and the optimal position of the trench layer. In addition, the optimization of the trench layer occurs when the trench is located below the pipeline. [9]

XiaobenLiua et al. (2020) used artificial neural network to predict the amount of strain on pipes on the fault, creating a finite element of pipelines subject to fault displacement to obtain a strain value database taking into account the influencing factors. The exact results obtained from this method show a good overlap compared to the results obtained from the main finite element methods. [11]

Nikoo et al. (2012) used evolutionary artificial neural networks to determine the displacement in the reinforced concrete structure. They accelerated a frame with a 4-story concrete wall with 4 openings in nonlinear dynamics analysis by IDARC2D software (ver.6.0) for 30 modes from 0.1g to 1.5g, then they determined the amount of damage using evolutionary model of artificial neural network. And showed that the MLP model has more appropriate capabilities than other models in terms of accuracy and flexibility of solving the equation and determining the displacement in reinforced concrete [12].

Abbasi et al. (2014) used artificial neural network models to predict the state of the continental shelf oil and gas pipelines. The pipelines are exposed to wear and tear. Therefore, it is very important that the pipelines are constantly monitored. The artificial neural networks (ANNs), which are technically based on the historical inspections of the three offshore oil and gas pipelines in Qatar, have been trained and developed. The models were able to predict pipeline conditions with a high accuracy of 99%. [5]

Zhang et al. (2020) used Bayesian network model for buried gas pipeline failure analysis. The pipeline failure caused by corrosion and external interference was analyzed. Failure frequency and leakage size were analyzed based on pipeline characteristics. A case study in the city of Hefei was used to state the practicability of the model. Finally, they showed that critical pipeline parameters can be identified using this model. [16]

Dawood et al. (2020) outlined the state-of-the-art of AI-based deterioration modeling for urban water systems. They also classified AI-based models were according to their contributions into seven categories. The models contributions, shortcomings, discussions, and critiques were provided. [17]

Ayati et al. (2019) studied a conceptual decision-making model, the Decision Table Method (DTM), for the measurement site design of pipe networks with the aim of inverse transient analysis. They proved that the main advantage of DTM is that even in case of large networks, calculation of the Hessian matrix and the utilization of any optimization algorithm is not required. They also evaluated the efficiency and applicability of the method on two pipe networks of small and large and compared the results with previous methods. eventually, the DTM is found reliable as well as easy to understand and implement. [18]

1.2. The Ramberg-Osgood Relationship

When the stress-strain relationship is not defined for the pipe material, it can be obtained as an approximation of the Ramberg-refractory relationship as follows:

$$\varepsilon = \frac{\sigma}{E}\left[1 + \frac{n}{1+r}\left(\frac{\sigma}{\sigma_y}\right)^r\right] \tag{1}$$

In which ε is strain, E is Young's Modulus, σ is stress, and n and r are constants which are selected based on the table 1.

Table 1. Ramberg- Osgood parameters

Pipe Class	Class B	X-42	X-52	X-60	X-70
Pipe Material yield Strength	227	310	358	413	517
n	10	15	9	10	5.5
r	100	32	10	12	16.6

1.3. Permissible Strain of the Pipeline

For oil and gas pipelines the maximum tensile strain should not exceed 4% in any case. For bends and T-joints maximum strain is restricted to 2%. The limiting compressive strain is considered according to the following formula:

$$\varepsilon_{cr-c} = 0.175\frac{t}{R} \tag{2}$$

Where *t* is thickness of pipe and *R* is radius of it.
More information on the permissible strain criterion for continuous underground pipelines are presented in the table 2.

Table 2. Permissible strain criterion for continuous underground pipelines

Permissible strain criterion for continuous underground pipelines			
Strain component	Pipe group	Permissible strain	
		stretching	compressive
continuous oil and gas pipeline	Ductile iron pipe Steel pipe PE pipe	2% 3% 20%	For PGD: At the beginning of the crease
	Pipe bends and tees	1%	To propagate the wave: 50% to 100 % Start of the crease (($\mathcal{E}_{cr-c}$)0.5 − 1)

2. ANSYS Finite Element Modeling

According to Figure (1), we model and show the soils around the pipeline, which includes several models of embankment, infrastructure and asphalt.

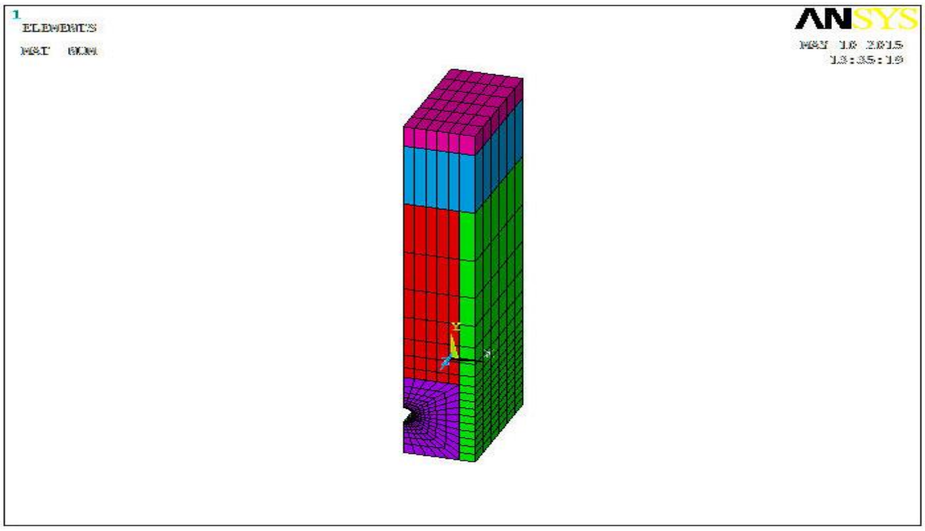

Figure 1. Three-dimensional overview of modeling and mesh for modeling different types of soil around the pipe

In this study, since the slip between the soil and the pipe is investigated, surface-to-surface contact is considered. The surface of the pipe is considered as the target surface and the soil surface is considered as the contactor surface. It should also be noted that the elements defined for the two contact levels in ANSYS software must have the same Real Constant number.

According to the capabilities of the software and also in order to reduce the computational costs and the number of solution equations in the finite element software and according to the symmetrical shape of the pipe as well as the loading forces, half of the pipe can be modeled.

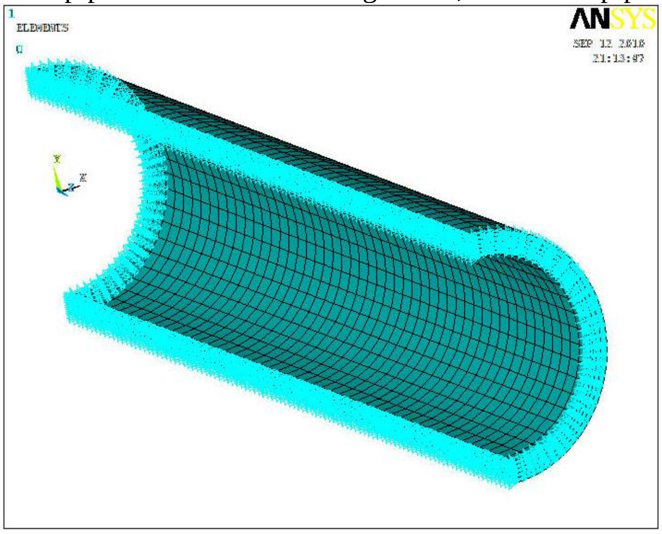

Figure 2. Three-dimensional mesh view for modeling contact elements and soil and half-pipe boundary conditions

The effect of internal pressure of 4 bar on the inner surfaces of the inner elements of the pipe has been carefully considered. According to Figure (3) modeling of pipe and soil and internal force of fluid, fluid force should be applied to each element.

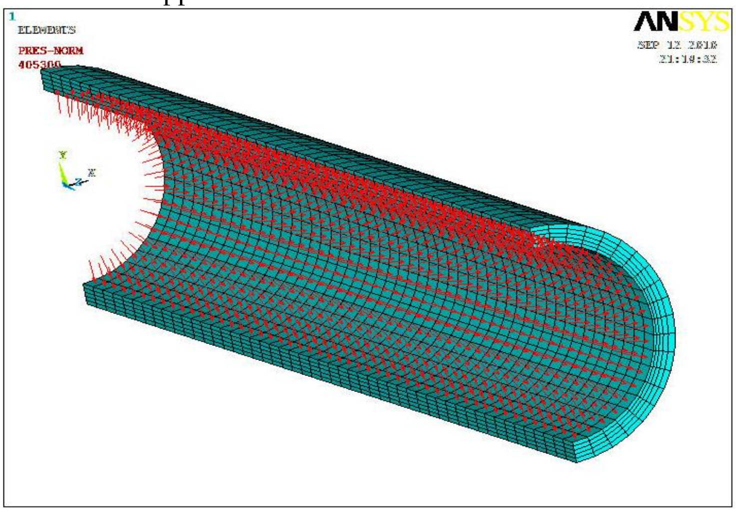

Figure 3. Modeling of pipe and soil and internal force of fluid

According to Figure (4) in this study, according to the descriptions presented, the Solid element is used to model the soil-pipe interaction.

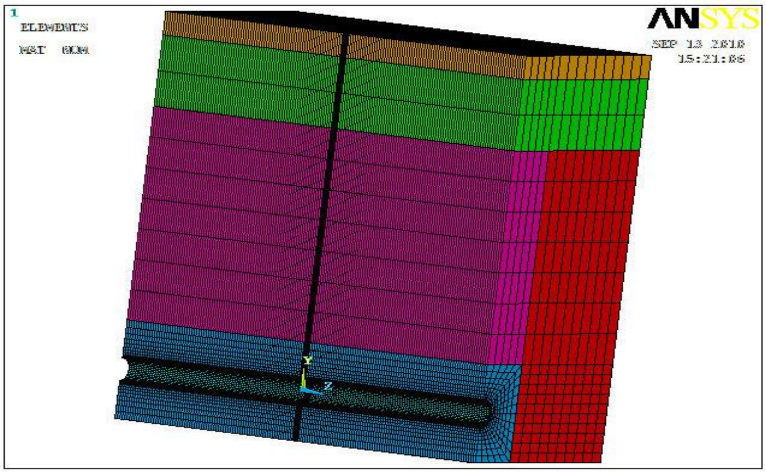

Figure 4. meshing of the pipe-soil model from the Solid element

Another set of coefficients of contact properties are values that correspond to the initial conditions of contact between surfaces. These coefficients and numbers include PMAX, PMIN, CNOF and ICONT, and starting the analysis alone or together creates the conditions for the initial contact between the surfaces and the reduction of the initial penetration between the levels. The contact parameters used in this research are given in the table below:

Table 3. The coefficients of the contact parameters used in the model

Constants	Value	Constants	Value
FKN	1	TAUMAX	1.1E+07
FTOLN	0.1	MU	0.1
ICONT	Closed gap/Reduce penetration	FACT	1

For finite element modeling, two types of elements were used. ANSYS element named “plane 183” used for modeling the pipe and “solid 95” element applied for soil. Plan 183 elements have been used as a guide for model construction. After creating three-dimensional Solid 95 elements, the two-dimensional elements have been removed from the model. According to Figures (5) and (6), the models become three-dimensional elements.

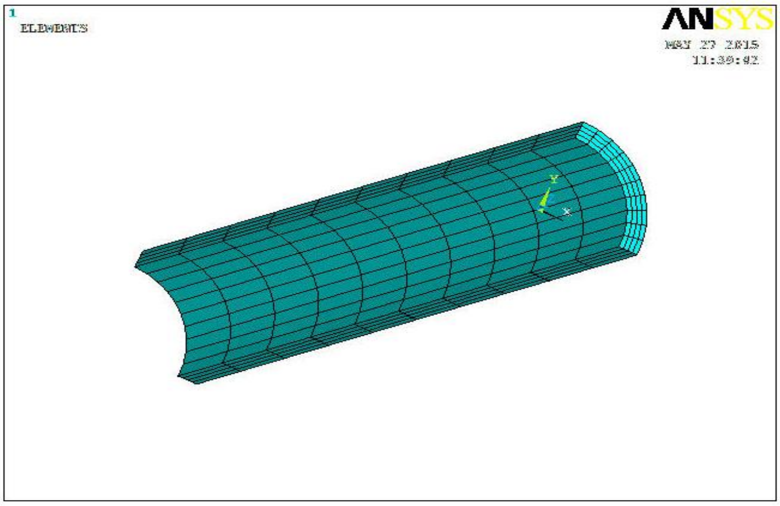

Figure 5. Mesh of the pipe model from the next element

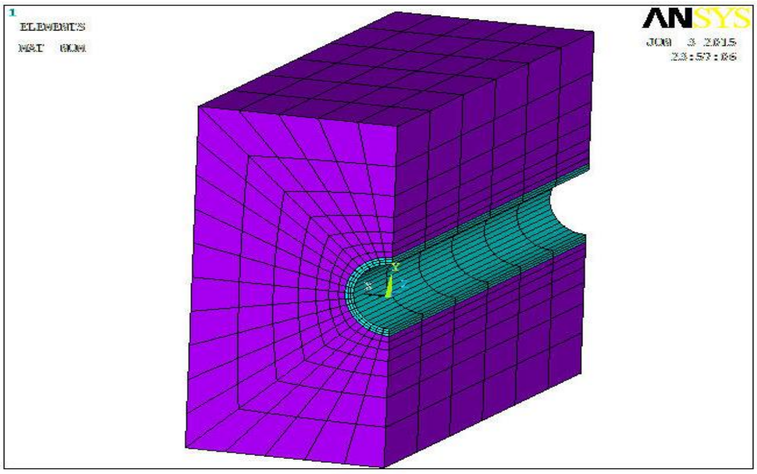

Figure 6. Mesh of the pipe-soil model from the next element

20-node bearings are very suitable for solving problems with curved surfaces, such as pipe-soil interactions. In the finite element models of the tube, only the title Material No. 1 has been introduced to ANSYS software and the physical properties of Linear elastic have been considered for it.

The boundary conditions applied to the nodes are as follows:

Bottom of the model on soil and coordinates:

$$y = -0.195^{m} \tag{3}$$

$$U_x = U_y = U_z = 0 \tag{4}$$

According to the geometric symmetry of the finite element model, only half of the body is modeled, so the boundary condition is as follows:

$$@ \;\; x = 0 \;\rightarrow\; U_x = 0 \tag{5}$$

That is, the displacement in the direction of the x-axis is zero in all nodes in the x = 0 coordinates.

Taking into account the assumption of plane strain plane strain for the model in the longitudinal direction of the pipe, the condition of zero displacements in the longitudinal direction is used at both ends of the pipe and the model, which is placed on the mentioned nodes. According to the created model (Figure (6)), this boundary condition has been applied in the following coordinates:

$$@\ z = 0 \rightarrow U_z = 0 \quad (6)$$

$$@\ z = 0.5 \rightarrow U_z = 0 \quad (7)$$

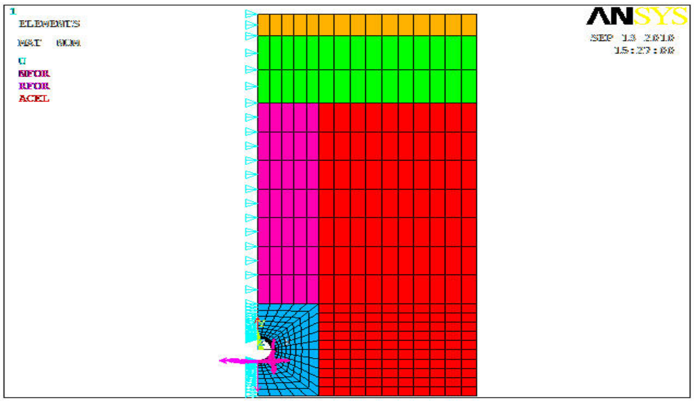

Figure 7. Three-dimensional mesh view to model the boundary conditions of soil and semi-pipes

It is noteworthy that the modeling has been done with special sensitivity regarding the distribution of elements and their small and large size as depicted in figure 7. As can be seen, the elements of the pipe and the surrounding soil are considered fine because the accuracy of the answers in this area is of particular importance. By moving away from the center of the pipe, due to the insignificance of the answers in that area and in order to save money in terms of software, larger elements have been used. The soil-structure interaction, is modeled using “CANTCT 174” ANSYS element and “SURF” contact element.

Different colors in figure 7 denote different types of materials in a heterogeneous medium. Table 4 describes the characteristics of these materials in detail.

Table 4. Properties of materials used

	Young’s Modulus	Poisson’s Ration	Density ρ (Kg/m^3)	Color
Mat No. 2 Soil Around the Pipe	4.8 Mpa	0.2	1600	Blue
Mat No. 3 Soil on top of the Pipe	6.9 Mpa	0.3	1900	Purple
Mat No. 4 Bedding Soil	6.9 Mpa	0.2	1700	Green
Mat No.5 Asphalt Layer	173 Mpa	0.35	2200	Orange

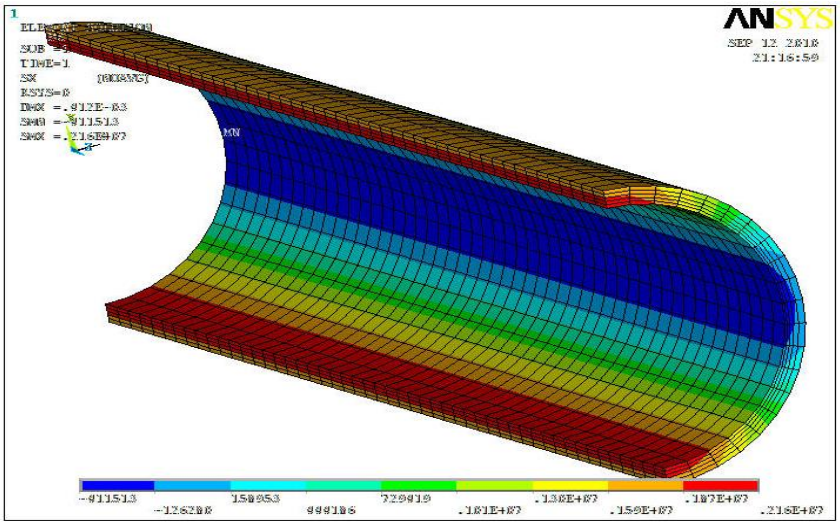

Figure 8. stresses obtained from pipe software analysis

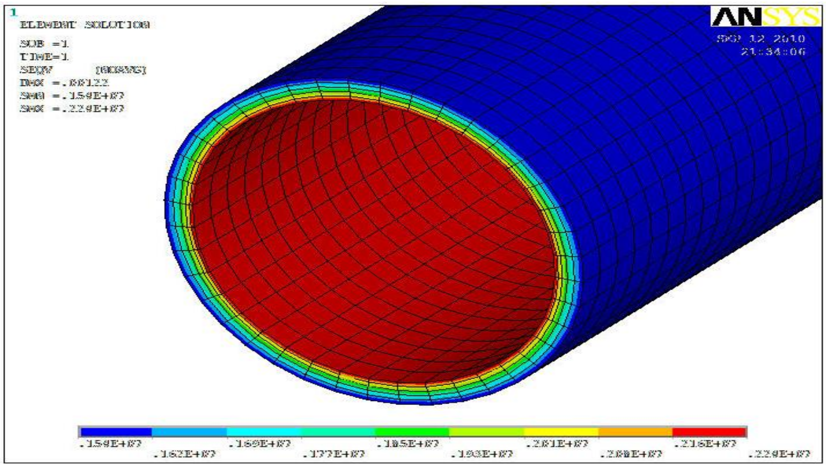

Figure 9. Three-dimensional overview showing the stress obtained from von Mice mode

3. Artificial neural network

Neural networks are a kind of simplistic modeling of real neural systems that have many applications in solving various problems in science. The application of neural networks includes many different areas, such as classification, interpolation, estimation, and detection, etc. Neural networks are a kind of simplistic Perhaps the most important advantage of these networks is their abundant capability along with their ease of use.

Presenting ANN as a tool for designing pipelines is the main focus of this article and ANSYS is used to produce the required data for ANN training and validation. deterministic and realistic model such as ANSYS is able to model the phenomenon, however, it is time consuming and needs hiring professional ANSYS users to create the model and interpreting the result. Moreover, like other FEM software packages, ANSYS is so expensive and is not affordable in many cases for small firms. ANN based codes and software can be found freely on the internet and are very simple to learn and use. So, in this study we suggest that a trained ANN can be an alternative to FEM based packages for designing buried pipelines.

This method can be readily applied for phase zero and phase one (feasibility study) of the pipe lines. In addition, it can be used for detailed design (phase two) if enough number of trainings data are available.

Finite element modeling input parameters were collected in a 39 x 753 matrix and outputs which are stress and strain were concluded in a 2 x 753 matrix. So for each training set there is 39 input parameter and 2 outputs. 70% of total data were used to train the model, 15% used for the validation and the last 15% applied for testing.

A fully connected feed forward network with 10 hidden layers with depicted architecture in figure 10 was created to model pipe line behavior. Due to the relatively difficult and complex dataset a Bayesian Regularization algorithm was selected as the training algorithm.

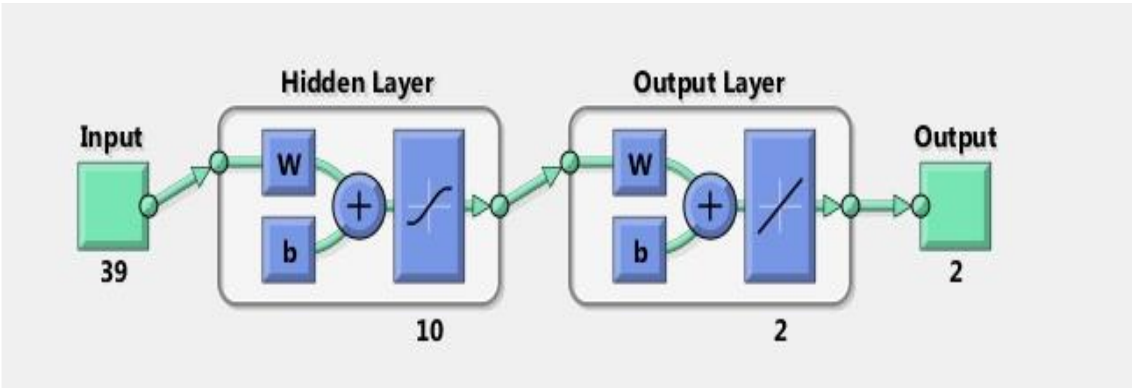

Figure 10. architecture of the neural network model with 10 hidden layer

The results of training, validation and testing of the model is shown in table 5. As shown in the table, the MSE error criterion is 0.045 and regression R value is 0.96 which imply that there is a good agreement between complicated and expensive ANSYS modeling result and presented neural network model.

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Table 5. Properties of materials used

	Samples	MSE	R
Training	527	0.009	0.998
Validation	113	0.000	0.967
Testing	113	0.045	0.959

An analysis on the epoch iteration numbers was done and the results shows that an epoch number more than 350 results in very low error (Figure 11).

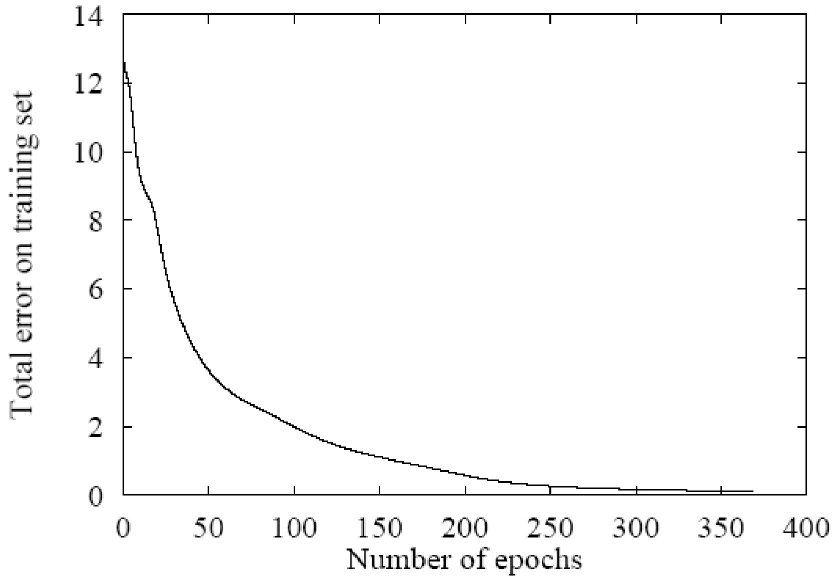

Figure 11. Learning or Error curve

To evaluate stress and strain results separately, the error of neural network model was calculated for each 113 datasets of the two output parameters. Figures 12 and 13, show strain and stress results compared to outputs of ANSYS finite element model. These diagrams show a very good agreement between the two methods. The MSE error for strain results is 0.0457 and stress error is 0.0453.

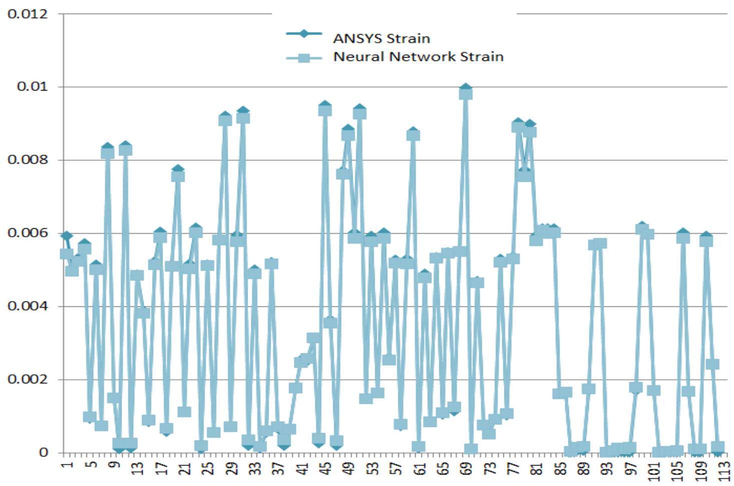

Figure 12. Diagram of a comparison of ANSYS strain results with the artificial neural network model

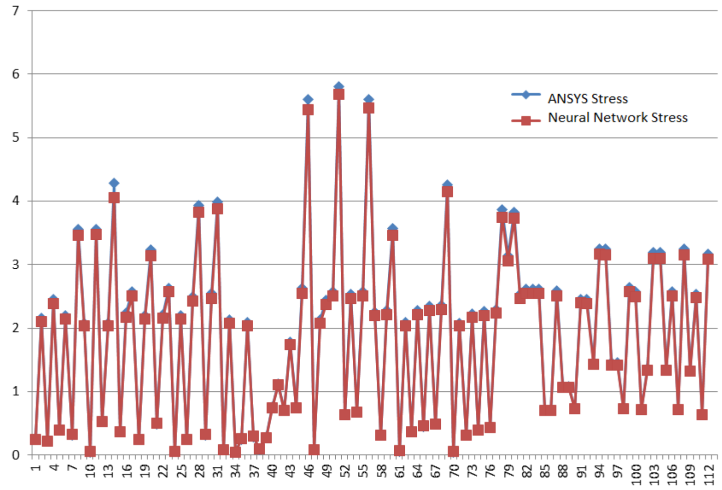

Figure 13. Diagram of a comparison of ANSYS stress results with the artificial neural network model

4. Conclusion

The results of this study show that the artificial neural network is able to design pipelines. Artificial neural network performs the design process much faster than ANSYS software. So consulting companies which are active in the field of pipeline design can use the artificial neural network due to very fast design process with several inputs including material, length, thickness, diameter, discharge and earthquake input parameters. This method can be readily applied for phase zero and phase one (feasibility study) of the pipe lines. In addition, it can be used for detailed design (phase two) if enough number of trainings data are available.

presenting ANN as a tool for designing pipelines is the main focus of this article and ANSYS is used to produce the required data for ANN training and validation. It is obvious that FEM based software packages like ANSYS are still outperforms ANN based algorithms for a detailed and complicated design, however, ANN possesses some advantages that makes it a good alternative to traditional methods at least for phase 0 and phase 1 design. ANN packages are readily available on the internet and their application is simple and it does not need a long and expensive training course. According to these advantages it can be predicted that suggested way of design will substitute the traditional methods in the future.

References

1. Barghi Kh, Asoudeh, H. (1391). Fragility analysis of buried pipelines against the effects of earthquake waves. 9th International Congress of Civil Engineering (p. 8). Isfahan: Isfahan University of Technology.
2. Bavanpour, H., Khazaei, J., & Sharafi, H. (2011). Numerical study of hazards resulting from the occurrence of earthquake-induced liquefaction on the site and stability of transmission pipes (vital arteries). Second National Conference on Crisis Management (p. 7). Tehran: Tehran.
3. Hosseinpour, S. (1389). Investigation of earthquake safety measures for pipelines in Tehran. Third Conference on Resilience and Urban Management (p. 8). Khomeini: Islamic Azad University, Khomeini Branch.
4. Fruits, M., Ghafouripour, A., & Karimi, A. (2010). Impact of earthquake on buried pipelines. The First National Conference on Crisis Management, Earthquake and Vulnerability of Vital Places and Arteries (p. 8). Tehran: Ministry of Interior, Crisis Management Organization.
5. Mohammed S. El-Abbasy, Ahmed Senouci, Tarek Zayed, Farid Mirahadi, Laya Parvizsedghy, Artificial neural network models for predicting condition of offshore oil and gas pipelines, Automation in Construction, Volume 45, September 2014,
6. Alireza Farhidzadeh, Ehsan Dehghan-Niri, Zilan Zhong, Salvatore Salamone, Amjad Aref, Andre Filiatrault, Post-earthquake evaluation of pipelines rehabilitated with cured in place lining technology using acoustic emission, Construction and Building Materials, Volume 54, 15 March 2014,
7. Meimei Liu, Min Yang, Modeling the behavior of natural gas pipeline impacted by falling objects, Engineering Failure Analysis, Volume 42, July 2014,
8. Chunlei Zeng, Changchun Wu, Lili Zuo, Bin Zhang, Xingqiao Hu, Predicting energy consumption of multiproduct pipeline using artificial neural networks, Energy, Volume 66, 1 March 2014,
9. Asskar Janalizadeh Choobbasti, Hamidreza Tavakoli, Saman Soleimani Kutanaei, Modeling and optimization of a trench layer location around a pipeline using artificial neural networks and particle swarm optimization algorithm, Tunnelling and Underground Space Technology, Volume 40, February 2014,
10. Do Hyung Lee, Byeong Hwa Kim, Hacksoo Lee, Jung Sik Kong, Seismic behavior of a buried gas pipeline under earthquake excitations, Engineering Structures, Volume 31, Issue 5, May 2009,
11. XiaobenLiuaQianZhengabKaiWuaYueYangaZiqiZhaoaHongZhan, Development of a novel approach for strain demand prediction of pipes at fault crossings on the basis of multi-layer neural network driven by strain data, Engineering Structures,Volume 214, 1 July 2020, 110685
12. Mehdi Nikoo, & Panam Zarfam . (2012). Determining Confidence for Evaluation of Vulnerability In Reinforced Concrete Frames with Shear Wall. Journal of Basic and Applied Scientific Research, 7(2), 6605-6614.
13. K. Kimishima1 , Y. Maruyama2 and F. Yamazaki3,SPATIAL DISTRIBUTION OF DAMAGES TO BURIED PIPES FOLLOWING THE 2007 NIIGATA-KEN CHUETSU-OKI, JAPAN, EARTHQUAKE, Proceedings of the 9th U.S. National and 10th Canadian Conference on Earthquake Engineering, Paper No 857, July 25-29, 2010

14. Numerical analysis of factors affecting the liquefaction caused by earthquake on the construction of buried pipes, Hassan Sharafi, Payam Parsafar
15. Guidelines for the Seismic Design of Oil and Gas Pipeline Systems, Committee on Gas and Liquid Fuel Lifelines of the ASCE Technical Council on Lifeline Earthquake Engineering, ASCE, American Society of Civil Engineers, New York, NY, 978-0-87262-428-3 (ISBN-13).
16. Y. Zhang, W.G. Weng, Bayesian network model for buried gas pipeline failure analysis caused by corrosion and external interference, Reliability Engineering & System Safety, Volume 203, 2020.
17. Thikra Dawood, Emad Elwakil, Hector Mayol Novoa, José Fernando Gárate Delgado,Artificial intelligence for the modeling of water pipes deterioration mechanisms, Automation in Construction, Volume 120, 2020.
18. Ayati, A., Ranginkaman, M., Bakhshipour, A., Haghighi, A. Transient Measurement Site Design in pipe networks using the Decision Table Method (DTM). Journal of Hydraulic Structures, 2019; 5(2): 32-48. doi: 10.22055/jhs.2019.29402.1107.
19. Dariane, A., Ashrafi Gol, M., Karami, F. Forecasting of rainfall using different input selection methods on climate signals for neural network inputs. Journal of Hydraulic Structures, 2019; 5(1): 42-59. doi: 10.22055/jhs.2019.29625.1113.
20. Alahdin, S., Ghafouri, H. Developing optimal operating reservoir rule-curves in drought periods. Journal of Hydraulic Structures, 2017; 3(2): 47-61. doi: 10.22055/jhs.2017.13490