Machine Learning for predicting pipeline displacements based on soil rigidity

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Abstract. This study investigates the impact of the soil rigidity on the mechanical behaviour for linear and nonlinear pipelines. The work is based on the results of a series of mechanical finite element analyses based on the VanMarcke and artificial neural network (ANN). The numerical model is validated based on the literature. Different simulations have been generated to obtain data response of the pipe based on displacement. The predicted results using ANN are compared with VanMarcke to prove the effectiveness and the importance of the probabilistic analysis. The analysis proves that the variation of the coefficient of subgrade reaction can induce a significant displacement of the pipe. The results prove that ANN serves a major role in the evolution of the real displacement of the pipeline and allows us to obtain more precise and interesting results based on both linear and nonlinear cases.

Keywords: Finite element analysis, Interaction sol-structure, Coefficient of subgrade reaction, numerical simulations, Static analysis, ANN approach, VanMarcke method.

1 Introduction

The pipelines are the innovative mean of energy and water transport, for that reason the study of the interaction soil-pipeline has been very attractive. In fact, a range of studies has been performed on the interaction soil-structure [1, 2]. The influence of the soil's nonlinear behaviour on different types of structures has been also studied [3, 4]. Dynamic analysis has been also performed to obtain additional observation and results on the soil-structure interaction problems [5]. For much improvement of the structure (beam, pipeline, plate…etc) design, a stochastic analysis has been done by different researchers [5-13] where the soil has been considered as heterogeneous. Grigoriu et al. [12] studied the behaviour of a beam on random soil,
Griffiths et al. [13] used a probabilistic method to analyse the response of the pile supported by Winkler random soil. Recently, several other numerical models of beam and pipeline resting on linear and nonlinear soil have been developed where the VanMarcke

method combined to Monte Carlo simulations has been used. Seguini and Nedjar [10-11] developed a simplified finite element model of soil-beam interaction based on the stochastic analysis in order to quantify the effect of different random soil parameters on the pipe response. This study has demonstrated the significant impact of the variation of the random soil's spatial parameters on the behaviour of the structure by the development of the displacement variations along the beam length. To investigate the non-linearity effect of the soil's on the behaviour of the beam, Seguini and Nedjar [14] performed a series of tests and simulations by using the nonlinear analysis [15-16]. In addition, recent research has been done on soil-structure interaction including the dynamic stochastic analysis of the pipeline [17-19]. In fact, Seguini and Nedjar [19] provided an accurate numerical modelling of the pipeline involving the seismic effect.

However, at later stage other probabilistic and optimization methods (the genetic algorithm the eXtended Iso Geometric analysis (XIGA) The Neural Artificial Network ANN-PSO) have been developed and used to identify the damage crack in different types of structures (beam and pipe) [20-23] Where the obtained results proved the efficiency of the ANN-PSO method on the crack identification.
The objective of this paper is in particular to expand the influence (effects) of the variation of the soil subgrade reaction on the response of the pipeline where the study is based on the results of a series of FEM obtained by using the VanMarcke method [24] which is compared with the data generated by ANN technique. The FEM was performed by using MATLAB. In fact, the new proposed fast approach allows us to optimize the results in order to obtain a more realistic pipeline's response.

2 Deterministic approach

However, in the following numerical analyses, the pipeline behaviour is considered to be nonlinear. Whereas the soil behaves according to elastic constitutive model [10]. The numerical approach is based on the von Kàrmàn method [15], [16] which has been used to represent the nonlinear behaviour of the pipeline (beam) [24]. Therefore, the governing equation of the pipeline (beam) resting on elastic soil is defined as follows [24]:

$$E_p I_p \frac{d^4 w_0}{dx^4} - \frac{3}{2} E_p A_p \left(\frac{dw_0}{dx}\right)^2 \left(\frac{d^2 w_0}{dx^2}\right)^2 + p(x) = q(x) \quad (1)$$

The soil reaction p(x) is given by the following formulation:

$$p(x) = k_{soil}.\pi.R_{ext}.w_0(x) \quad (2)$$

k_{soil} is the modulus of the subgrade reaction of soil, R_{ext} , Ip and Ep is respectively the half-perimeter, the inertia and the Young's modulus of the pipe. $w_0(x)$ is the polynomial displacement function which depends on the vector N composed of Hermite cubic interpolations functions and on the vector of the nodal displacements Δ^e (e represents an element of a discretized pipeline).

The differential equation (1) is resolved by using the total potential energy functional:

$$\Psi = \Psi_1 + \Psi_2 \tag{3}$$

Ψ_1 and Ψ_2 are respectively the strain energy of the pipe and the soil.

$$\Psi_1 = \frac{1}{2}\{\Delta^e\}^t \left\{ \left[\frac{1}{4} E_p^e A_p^e \left(\frac{w_2 - w_1}{l_e} \right)^2 \int_0^{le} \left(\frac{dN}{dx} \right) \left(\frac{dN}{dx} \right)^t dx \right] + \left[E_p^e I_p^e \int_0^{le} \left(\frac{d^2N}{dx^2} \right) \left(\frac{d^2N}{dx^2} \right)^t dx \right] \right\} \{\Delta^e\} \tag{4}$$

$$\Psi_1 = \frac{1}{2}\{\Delta^e\}^t \left[K_{pnl}^e \{\Delta^e\} + K_{pl}^e \right] \{\Delta^e\} \tag{5}$$

$$\Psi_2 = \frac{1}{2}\{\Delta^e\}^t \left(k_{soil}.\pi.R_{ext}.\int_0^{le} \{N\}.\{N\}^t dx \right) \{\Delta^e\} \tag{6}$$

$$\Psi_2 = \frac{1}{2}\{\Delta^e\}^t [K_{sl}^e] \{\Delta^e\} \tag{7}$$

Finally, the following incremental equation (8) is solved by using Newthon-Raphson method [24].

$$\left[K^e \{\Delta^e\}^i \right] \{\Delta^e\}^{i+1} = \{F\} \tag{8}$$

$$\{\Delta^e\}^{i+1} = \{\Delta^e\}^i + \{\delta\Delta\} \tag{9}$$

where $\{F\}$ and $[K^e]$ are the element force vector and the element rigidity matrix respectively as defined in Ref [24].

3 Probabilistic approach

3.1 VanMarck's method

The VanMarcke approach [25, 26] is based on the local average method where the random coefficient of soil's subgrade reaction k_{soil} is characterized by a lognormal distribution. Their local average and variance are defined respectively as follow:

$$E[k_{soil}(D_i)] = m_k \tag{10}$$

$$Var[k_{soil}(D_i)] = \sigma_k^2 \gamma(D_i) \tag{11}$$

where the variance function γ(Di) is written as

$$\gamma(D_i) = \frac{2}{D_i}\int_0^{D_i}(1-\frac{x}{D_i})\rho(x)dx \tag{12}$$

with $\rho(\tau) = 1 - \frac{|\tau|}{L_c}$ for $|\tau| \leq L_c$ (13)

The discretization form of the variance function γ(Di) is defined as follow:

$$\gamma(D_i) = \begin{cases} 1 - \frac{D_i}{3L_c} & if \quad D_i \leq L_c \\ \frac{L_c}{D_i}\left(1 - \frac{L_c}{3D_i}\right) & if \quad D_i \succ L_c \end{cases} \tag{14}$$

In order to compute the covariance matrix C_{ij} of the coefficients of soil's subgrade reaction we use the local average method defined by Fenton and VanMarcke [27].

$$C_{ij} = Cov\left[k_{soil}(D_i), k_{soil}(D_j)\right] \tag{15}$$

$$C_{ij} = \frac{\sigma_k^2}{2}\left\{(t-1)^2\gamma[(t-1)D] - 2t^2\gamma[t.D] + \{(t-1)^2\gamma[(t-1)D] - 2t^2\gamma[t.D] + (t+1)^2\gamma[(t+1)D]\}\right\} \tag{16}$$

(*i*) and (*j*) are the zone indices where t=|*i* - *j*|. The zone's length *D*=*Di*=*Dj*.

3.2 ANN

The Artificial Neural Network (ANN) is an optimization method based on biological nervous systems. Many researchers have used this method for classification, identification and control system...etc. Therefore, the goal of this approach is to combine the problem with optimizations to improve performance and find the best results in order to determine the real response and very fast compared with FEM and analytical solution. In this work, the ANN method based on three components: an input layer, hidden layer, and output layer as represented in Fig.1.

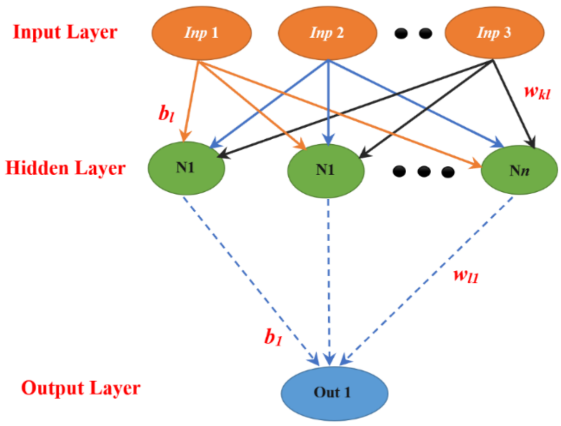

Fig.1. Schema of the Artificial Neural Network (ANN) method.

w_{kl} is the weights of neuron connection between input node and neuron in the hidden layers.
b_l is the bias and w_l is the weights of neuron connection between neuron in hidden and output layers. b_1 is bias associated with the single neuron in the output layer. Indices $Q = 1, 2, \ldots, m$ is the number of collected data and $S= 1, 2, \ldots, n$ is hidden layer neurons. The total number of parameters (weight and biases) employed in the network is $n\times (m + 2) + 1$.

Once the structure of the ANN model has been built, training with input and output sets are conducted to find the appropriate weights and biases and can be improved by optimization techniques as defined in Ref [28]. Therefore, the objective is to minimize the difference between the results obtained from VanMarcke method and ANN approach by using the root-mean-square error (RMSE) function which is defined as follows

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{s=1}^{n}(O_S - l_S)^2}{nd}} \quad (17)$$

O_s is the output corresponding to l^{th} data point in the training set by the network,
l_S is the actual output as consider in the target set,
nd is the number of data point considered in training data-set.

4 Numerical analysis

As for numerical study on the soil-pipeline interaction, the heterogeneity of the soil and the nonlinearity of the pipe has been considered and discretized on 63 elements. A finite element model of Seguini and Nedjar [18] has been optimized by using a new probabilistic method (NNE). The nonlinearity of the pipe and the soil have been taken into account by using the Von Karmàn method to simulate (represent) the beam [24] and the learning machine method to optimize the results in order to obtain the real response of the pipeline. Fig 2, presents the validation of a numerical model with Ref [29].

Table 1. Pipeline and Soil Properties [24].

Symbol	Parameters	Range of values	Unit
D_{ext}	Diameter of the pipe	1	m
L_p	Length of the pipe	62	m
E_c	Pipe elastic Young's modulus	3 x10^4	MPa
E_cI_c	Pipe Flexural rigidity	869.45	MN/m^2
v_p	Poisson ration of pipe	0.2	(-)
kw	Coefficient of Winkler soil's subgrade reaction	3.067	kN/m^3
v_p	Poisson ratio of soil	0.35	(-)
E_s	Soil elastic Young's modulus	12.5	MPa

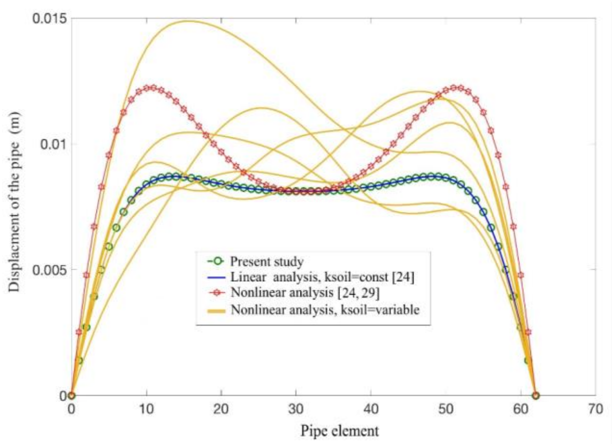

Fig. 2. Linear and nonlinear analysis of pipeline resting elastic soil with k_{soil} =constant and k_{soil}=variable.

4.1 Results

After validation of our numerical method as done in Ref [24] by comparing the linear and nonlinear response of the pipeline as shown in Fig 2, we use the NNE method in order to optimize the results. For the linear analysis the coefficient of subgrade reaction of soil is considered constant and for the nonlinear case, the k_{soil} is variable. Therefore, from Fig 2 we can deduce that the VanMarcke 's method combined to Monte Carlo simulations allows us to obtain a higher displacement of the pipe when the value of k_{soil}

change (variable). So, it can be noted that the real response is obtained by using the probabilistic approach. The training after collecting the data using ANN is presented in Fig 3.

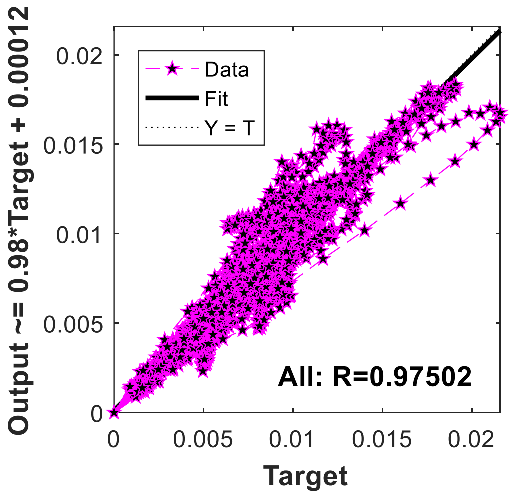

Fig. 3. Training using ANN.

Six scenarios are predicted using ANN after training in both cases linear and nonlinear.

Scenario 1. **Linear Problem**

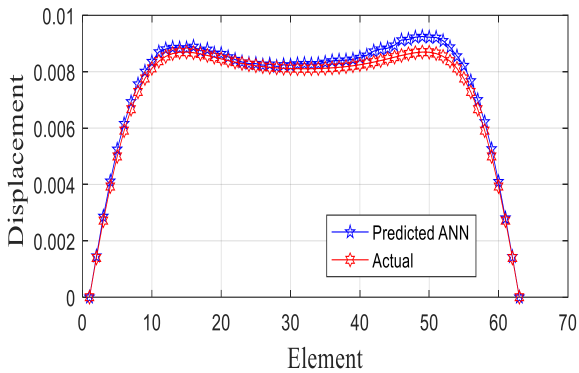

Fig. 4. Scenario 1 predicted using ANN.

Scenario 2. **Nonlinear Problem**

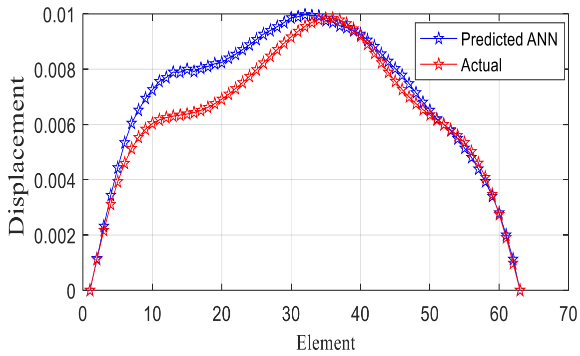

Fig. 5. Nonlinear Problem, Scenario 2.

Scenario 3. **Nonlinear Problem**

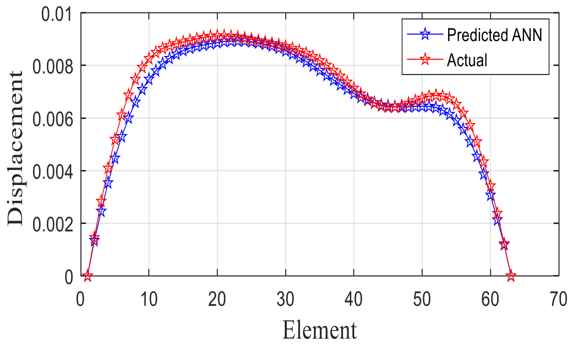

Fig. 6. Nonlinear Problem, Scenario 3.

Scenario 4. **Nonlinear Problem**

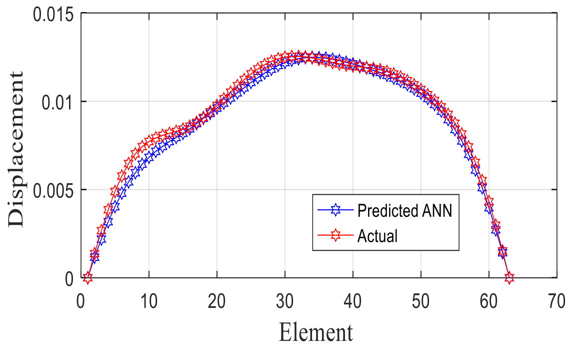

Fig. 7. Nonlinear Problem, Scenario 4.

Scenario 5. **Nonlinear Problem**

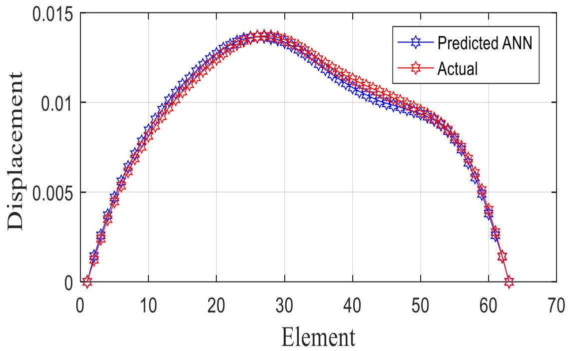

Fig. 8. Nonlinear Problem, Scenario 5.

Scenario 6. **Nonlinear Problem**

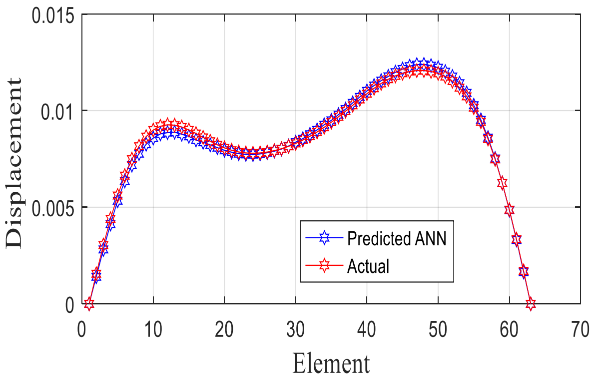

Fig. 9. Nonlinear Problem, Scenario 5.

The provided results are more accurate compared with reference results.

5 Conclusion

In this paper, the impact of the soil rigidity on the mechanical behaviour for linear and nonlinear pipelines is investigated. The objective is to predict the displacement of pipe using machine learning using ANN. The numerical model is validated based on data from the literature. Different simulations have been generated to obtain data response of the pipe based on displacements. The predicted results using ANN are compared with VanMarcke to prove the effectiveness and the importance of the proposed application. The analysis proves that the variation of the coefficient of subgrade reaction can induce a significant displacement of the pipe. The results prove that the ANN has more accuracy to predict the displacement sof the pipeline in both linear and nonlinear cases.

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