Applied Radiation and Isotopes 141 (2018) 44–50

Contents lists available at ScienceDirect

Applied Radiation and Isotopes

journal homepage: www.elsevier.com/locate/apradiso

Inorganic scale thickness prediction in oil pipelines by gamma-ray attenuation and artificial neural network

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HIGHLIGHTS

- A method based on the principles of gamma densitometry is presented.
- Theoretical models for different scale thickness are developed using the MCNP-X code.
- The system uses the ^{137}Cs source and NaI(Tl) detector to predict the scale thickness.
- The scale thickness is calculated by an algorithm given by an ANN.

ARTICLE INFO

Keywords:
Gamma transmission
Scale
Artificial neural network
MCNP-X code

ABSTRACT

Scale can be defined as chemical compounds that are inorganic, initially insoluble, and precipitate accumulating on the internal walls of pipes, surface equipment, and/or parts of components involved in the production and transport of oil. These compounds, when precipitating, cause problems in the oil industry and consequently result in losses in the optimization of the extraction process. Despite the importance and impact of the precipitation of these compounds in the technological and economic scope, there remains difficulty in determining the methods that enable the identification and quantification of the scale at an initial stage. The use of gamma transmission technique may provide support for a better understanding of the deposition of these compounds, making it a suitable tool for the noninvasive determination of their deposition in oil transport pipelines. The geometry used for the scale detection includes a 280-mm diameter steel tube containing barium sulphate ($BaSO_4$) scale ranging from 0.5 to 6 cm, a gamma radiation source with divergent beam, and a NaI(Tl) 2 × 2″ scintillation detector. The opening size of the collimated beam was also evaluated (2–7 mm) to quantify the associated error in calculating the scale. The study was done with computer simulation, using the MCNP-X code, and the results were validated using analytical equations. Data obtained by the simulation were used to train an artificial neural network (ANN), thereby making the study system more complex and closer to the real one. The input data provided for the training, testing, and validation of the network consisted of pipes with 4 different internal diameters (D1, D2, D3, and D4) and 14 different scale thicknesses (0.5 to 7 cm, with steps of 0.5 cm). The network presented generalization capacity and good convergence, with 70% of cases with less than 10% relative error and a linear correlation coefficient of 0.994, which indicates the possibility of using this study for this purpose.

1. Introduction

In the oil industry, the production of oil and natural gas involves the transport of fluids in liquid and gaseous phases to a processing unit where a phase separation is performed. This separation is in the interest of the industry and has as its objective the greatest proof of the natural good, oil. In recent years, however, oil production operations have been expanding to ever greater depths, thus making the associated costs even higher and also making very necessary detailed studies of feasibility and optimization of equipment and processes related to the transportation of multiphase fluids under these conditions.

During the process of formation of oil and gas, already allocated in reservoir rocks, there is also a production of water called formation water. This presents characteristics inherent to the rock to which it is located, and its quantity will depend on the characteristics of the natural or artificial mechanisms of production and the composition

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https://doi.org/10.1016/j.apradiso.2018.08.008
Received 16 November 2017; Received in revised form 31 July 2018; Accepted 9 August 2018
Available online 10 August 2018
0969-8043/

characteristics of the reservoir rock itself. The water produced from the reservoir rock is identified by its salinity and chemical composition (Beserra, 2012). To maintain the pressure conditions in the reservoir rock, a water injection operation can be carried out in the lower layers of the rock, favoring the migration and collection of the natural material of interest to the wells.

During oil extraction, water and sediments are also extracted, which mix with the oil, and this together with changes in pressure, temperature, and fluid flow can cause these elements to precipitate, thereby forming deposits of scale on the walls of the pipes. Because of the chemical affinity of the elements soluble in the sea water and the formation water, chemical reactions may occur that will favor the formation of inorganic deposit, the scales.

Fouling may cause reduction in internal pipe diameters due to the accumulation of deposited products, drilling at pipe points and equipment due to corrosion-promoting agents, and increased energy consumption due to reduced equipment efficiency and shortened life of equipment and installation (Fiorentin, 2004).

Scales of barium, strontium, and calcium, for example, are usually formed by the mixture of formation water and injection water. When the high concentration of sulphate anions present in the injection water interacts with the high concentration of divalent cations (Ba^{2+}, Sr^{2+} e Ca^{2+}) present in the formation water under favorable thermodynamic conditions, sulphate salt precipitates may be formed, as shown in Fig. 1.

Over time, these salts gradually deposit on the walls of the pipes and equipment used in the extraction and transport of oil/gas, thus contributing to decrease in the internal diameter of the pipes and may even obstruct passages and damage equipment, necessitating periodic maintenance actions, such as cleaning or even tube replacement (Martin et al., 1997). Thus, scale causes economic losses because of the large impact on operating costs and equipment performance in offshore operations (Allen and Roberts, 1982).

Scale depositions limit and sometimes block the production of oil and gas by obstructing the oil formation matrix. It can also damage production lines and equipment and interfere with the fluid flow. This directly results in the failure of production equipment, emergency shutdowns, increased maintenance cost (predictive and corrective), and general decrease in production efficiency (Oliveira, 2009). In this sense, there is a need to deepen the studies as a way of identifying and quantifying the fouling to evaluate the corrective and preventive measures.

By using conventional technology, fouling detection occurs by monitoring changes in pressure and temperature at certain points in the industrial plant, which indicate only the occurrence of the problem, most of which are already at an advanced stage (Marinho et al., 2008). In addition, the sensors used are expensive because of the high installation and maintenance costs, because they must be in contact with the fluid, which can be abrasive/corrosive and can cause physical damage to the sensors used, thus increasing the periodicity of recurring exchanges.

Fig. 1. Pipe used in oil platform encrusted with barium sulphate (OLIVEIRA, 2009).

Nuclear techniques, which are noninvasive, have been a potential solution for the preventive control and monitoring of scale evolution and are mainly used to monitor and quantify fouling in the offshore environment.

From the economic point of view, nondestructive testing procedures seem to be promising in the evaluation of deposits (Marinho et al., 2008). Once a system is in place and in perfect working order, it is often not wise to interrupt it to conduct a study. In practice, there are relevant difficulties in obtaining results by performing destructive examinations. In fact, the advantages of a nondestructive testing is that it can often be performed at convenient times and does not necessarily interrupt the operations.

Gamma-ray densitometry, one of the nondestructive test methods, has been used for many years, and satisfactory results have been obtained in different industries, such as petrochemical, oil, and mining (Salgado et al., 2013; Roshani and Nazemi, 2017). It has been used for flow measurement studies (Mi et al., 1998; Salgado et al., 2009), density prediction (Achmad and Hussein, 2004; Salgado et al., 2016), thickness measurements (Candeias, 2010; Beserra, 2012; Majid, 2013; Soares, 2014; Oliveira et al., 2014), oil transport monitoring applications (Khorsandi and Feghhi, 2011), and fouling and corrosion detection in pipes used for oil extraction (Monno, 1985; Mcconn et al., 2011).

This technique makes use of radioactive sources of gamma rays, and by using them it is possible to obtain measurements without, however, modifying the operating conditions of the system under study, thus allowing to carry out the whole process of monitoring. Nuclear techniques based on gamma-ray absorption methods can provide reliable measures of thickness fluctuation, for example, by improving accuracy and reducing costs. However, in this type of measures, difficulties are encountered, such as the presence of water, gas, or oil due to differences in their density interferes with the accuracy in estimating the scale thickness. Thus, there is a need to evaluate the behavior of the radiation beam in the most realistic scenario possible, that is, considering the influence of the fluids in a tube-fouling-fluid system.

Analysis by transmission measurements can be achieved by comparing the signals recorded by the detector with the content of a density calibration table or by using analytical equations. In any case, the calibration table can be influenced by important parameters that depend on the measurement conditions, such as pipe diameter, pipe wall thickness, temperature, and pressure, and even errors caused by the calibration procedure itself (Maucec and Denijs, 2009). It is necessary to investigate the impact of these parameters on the density measurement. In both procedures, simplifications, based on experimental data, are often performed on the analytical model to obtain an approximate solution; however, this may lead to large errors because of the changes in flow regime occurring in time and space. In addition, the solution to analytical equations is specific to a given flow regime and measurement geometry, and obviously, there can be no significant changes in the system for the solution to have any meaning.

Theoretical, representative static models are developed using the mathematical code MCNP-X based on simulations using the Monte Carlo method. The code is used to provide an artificial neural network (ANN) training set formed by different fouling thicknesses and different internal diameters of the pipe.

Techniques using gamma ray sources and ANNs are applied to interpret the pulse height distributions (PHDs) obtained by a radiation detector to determine the fouling thickness in pipes used in oil production. The proposed ANN can correctly predict the fouling thickness of the pipes considering the presence of the fluids with satisfactory results in systems containing water, gas, and oil.

2. Theoretical foundations

2.1. Scale in oil pipelines

During the oil production process, the drilling and the consequent transport of the oil are done through the injection of water. This method aims at the maximum oil recovery and the pressure stability of the reservoir rock selected for oil removal. In marine oil fields, the water used is essentially sea water, rich in sulphate anions (SO_4^{2-}), because of its availability and low costs associated with production, and it can undergo previous treatments before being injected into the bed rock. The mixture of injected water and the formation water rich in barium divalent ions may favor the precipitation of barium sulphate, the precipitate being most commonly found in the equipment/pipes because of its higher proportions in the formation water.

There are other factors such as the variation in thermodynamic conditions that can also cause salt precipitation and consequent deposition. The pressure, temperature, concentration, and pH, for example, may change during the oil production process; this favors scale formation.

Considering the diversity of processes involved in the initial stages of oil processing and that the precipitation of the salts occurs in these phases, it is noted that the precipitation of these salts has a considerable impact, not limited only to the reduction of the passage of fluids in the pipes but also in a series of associated operational problems. In view of this, countermeasures are necessary to avoid or reduce them.

2.2. Photon beam attenuation

The method developed in this work, based on gamma-ray attenuation measurements, presents high sensitivity to the atomic number (Z) of the material, mainly at low gamma-ray energy. The attenuation coefficient for photoelectric effect at a given photon energy is highly dependent on both the atomic number and the density of the absorbing material.

The linear attenuation coefficients for barium sulphate, iron, and fluids were determined by transmitting a monoenergetic pencil beam according to the Beer–Lambert law, which is shown as Eq. (1).

$$I = I_o * e^{-(\mu_p * W_p + \mu_F * W_F + \mu_S * W_s)} \tag{1}$$

Where

I: intensity of uncollided photons ($\gamma\,cm^{-2}\,s^{-1}$);
Io: intensity of primary photons ($\gamma\,cm^{-2}\,s^{-1}$);
μ: linear attenuation coefficient (cm^{-1});
w: beam path length through the absorber (cm);
P – pipe, F – fluid, S – scale.

2.3. MCNP-X code

MCNP-X code is a computational tool based on a statistical method of understanding complex physical or mathematical systems using randomly generated numbers as inputs into these systems to generate a range of solutions. The probability of a specific solution can be found by dividing the number of times the solution was generated by the total number of tests. By conducting a high number of tests, the probability of solutions can be determined with greater precision. The Monte Carlo method is mainly used in problems where the determination of an analytical solution would be difficult or even impossible. It can be applied to studies involving radiation transport for simulating the individual particle trajectories and the processes inherent in the interaction of radiation with matter by generating pseudo-random numbers, as a function of the distribution of probability governing the physical processes of scattering, absorption, capture, etc. (Pelowitz, 2005).

The MCNP code has different versions; in 1983, the Monte Carlo N-Particle version 3 (MCNP-3) code was entirely rewritten using FORTRAN 77 and released to the scientific community (Beserra, 2012). In computational codes used for some simulations, the material media are considered homogeneous with constant density. The atoms and molecules are distributed statically. Thus, the dynamic effects of the environment are disregarded (Beserra, 2012).

The Monte Carlo N-Particle eXtended computational code – MCNP-X – is widely used in the study of radiation transport and interaction with matter, involving neutrons, photons, electrons, and even other particles. It features the ability to handle complex three-dimensional geometries and a variety of input data options, making it a versatile and powerful tool when applied in the field of radiation protection, modeling of measurement equipment, and nuclear installations (LANL, 2003).

2.4. Artificial neural network (ANN)

An ANN can be defined as an intense processor-parallel distributed system, whose processing units are very simple, that have the natural propensity to store knowledge and make it available for use.

An ANN is formed by processing units connected to each other, called artificial neurons. Each neuron is responsible for reading input and output data through mathematical (usually nonlinear) functions. In the context of signal transmission between neurons, two distinct ANN activities may occur:

i) Learning or training: the stimuli (input data) and output signals (output data) are simultaneously submitted to the neurons for the learning phase.
ii) Use of knowledge: a set of neurons that has undergone previous learning is exposed to new stimulus. Such input stimulus, new and different from those used for learning, will be treated by trained neurons. They result in output data corresponding to the new stimulus. Ultimately, the output data are a consequence of previous learning.

In this work, a multilayer perceptron (MLP) feedforward ANN is used, with a backpropagation algorithm, to predict the thickness of the scales with different internal diameters of the pipe. MLPs is a class of feedforward ANN that consists of at least three layers of nodes. Backpropagation is a method used in ANNs to determine a gradient that is needed in the calculation of the weights to be used in the network.

3. Methodology

The present section describes the study of the gamma transmission method using the Monte Carlo N-particle (MCNP-X) code and the method used to predict the thickness of concentric inorganic scale of barium sulphate in oil pipes.

3.1. Simulated geometry

The detection geometry consists of a 2 × 2" NaI (Tl) scintillation detector, positioned at 180° from a point source of ^{137}Cs (662 keV) gamma rays. Considering that the analytical equations used for calculating thickness are valid for a pencil beam, a study of source divergence was carried out with the objective of optimizing the source activity and evaluating the associated errors in the scale calculus. The divergence established initially for the source was 5.73°, which corresponds to a collimator with a 2-mm aperture in the geometry established in this work. To evaluate the influence of the divergence of the source, the opening of the collimator was varied: 2 mm, 4.5 mm, and 7 mm. The most appropriate value for the collimator opening, after the simulations, will be used in the scale calculation.

A source, also punctual, pencil beam is also used for comparative

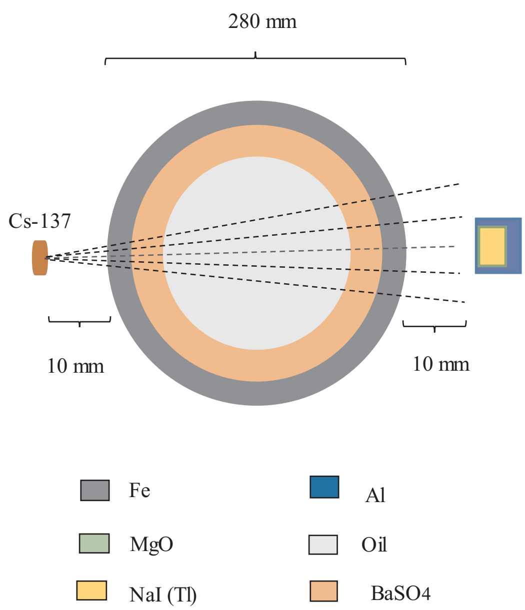

Fig. 2. Simulated system.

purposes, and all these tests were performed using the MCNP-X code. It should be noted that the source divergence is mathematically developed with the desired emission, without the use of an actual collimator, using the commands provided in the MCNP-X code. The pipe used is essentially made of iron and has a thickness of 5 mm and an external diameter of 280 mm. The fluid used is crude oil. To obtain the scale thickness, its value from 0,5 to 6 cm containing concentric scales and formed by only $BaSO_4$ was varied, as shown in Fig. 2.

The simulation responses were obtained using the output commands available in the code, to study the influence of the collimator using the command to current integrated over a surface (F1, tally card), while the command (F8, tally card) to calculate the energy distribution of pulses created in a detector (MeV) was used for the study of the scale value. These commands display a relative error due to counts in each spectrum energy range. The number of histories (NPS) used was determined to obtain acceptable statistics, with relative error values lower than 5% for 662-keV energy, according to the MCNP-X manual (Pelowitz, 2005).

3.2. Calculation of the scale thickness

The scale thickness in different positions of the source-detector system was calculated using analytical equations based on trigonometric relations. To obtain the scale thickness values, mathematical relations are necessary to delimit the path that the radiation will go through in each material that composes the system to be studied and to relate that path covered with the thickness of the scale (Oliveira, 2009).

Fig. 3 shows the arrangement of the source-detector system with references used to calculate the radiation path.

h: height of position 1 of the source-detector system;
CD: straight line to position 1 of the source-detector system;
R: external radius of the pipe;
r: internal radius of the pipe;
AD: radiation path in scale (W_{INC}) to position 1 of the source-detector system;
AB: scale thickness (X_{INC}) for position 1 of the source-detector system;
P1: position 1 of the radioactive source;
D1: detector 1, NaI scintillator (Tl).

The pipe can be considered as an absorber system composed of n

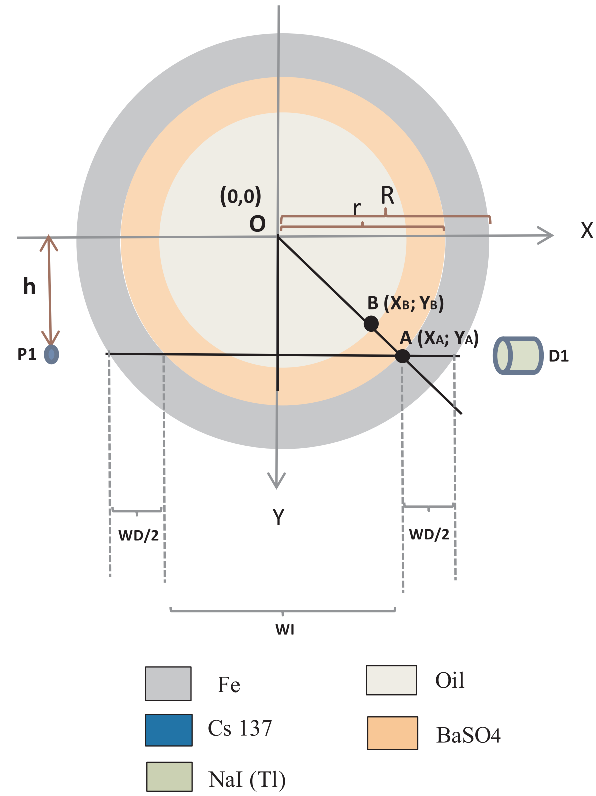

Fig. 3. Representation of the trigonometric relationships of the pipe, fluid (oil), and concentric incrustation.

layers of materials with different thicknesses and attenuation coefficients. The intensity (I) of a monoenergetic beam of transmitted γ radiation can be estimated by Eq. (1). This equation, together with the paths traveled by the radiation in each absorber material (pipe, fluid, and scale), can be written in a simple way as follows (Eq. (2)):

$$W_{INC} = \frac{\ln(K) + \mu_D.\ W_D + \mu_F.\ W_I}{-\mu_{INC} + \mu_F} \tag{2}$$

K: gamma transmission, given by the ratio I/I_0;
μX: transmission coefficient (cm^{-1});
Wx: radiation path: D – pipe; F – fluid, and INC – incrustation (cm);
WI: path of radiation in the fluid and incrustation (cm).

Points A and B can be obtained by cartesian coordinates, represented by x_a, y_a, x_b, y_b, respectively. Once all the coordinates related to the AB segment are obtained, the scale thickness (W_{INC}) for a given position i of the detector can be obtained by Eq. (3).

$$AB = \sqrt{(x_a - x_b)^2} + \sqrt{(y_a - y_b)^2} \tag{3}$$

For mathematical validation of the model developed by the MCNP-X Code, scale thickness values were obtained for 8 different source-detector height positions, moving the detection system from 3 to 6.5 cm, in steps of 0.5. After this mathematical validation, the model was used to train an ANN.

3.3. ANN training

The principle of obtaining the thicknesses is based on correlating the counts recorded in the detector with the variation in the scale thickness. In this work, the scale thickness was calculated using an algorithm given by an ANN. The ANN training consisted of providing a set of training data that has the following proportion: approximately 60% training, 30% test, and 10% production. A set of input data was

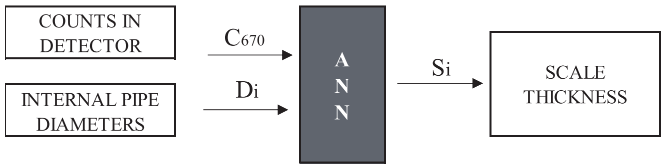

Fig. 4. Representation of the process for ANN training and learning.

Table 1
Linear attenuation coefficients for pipe, incrustation, and oil.

Data	Duct	Scale	Oil
Density (g/cm^3)	8	2.6	0.973
Linear attenuation coefficient (MNCP-X)	5.78E − 01	1.90E − 01	7.75E − 02
Linear attenuation coefficient (NIST)	5.80E − 01	1.96E − 01	8.38E − 02
Relative error (%)	− 0.29	− 3.12	− 7.51

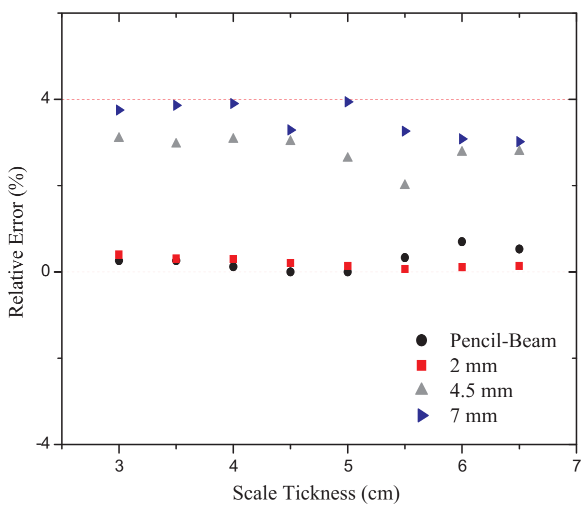

Fig. 5. Scale thickness for collimation openings.

provided to the ANN with 60 cases, which were submitted to training and learning. All the data were empirically distributed between training, testing, and validation. Fig. 4 shows a generic representation of the ANN training and learning process. It is worth noting that the ANN training pattern is composed of inputs and outputs. As observed, the inputs and outputs for training the network are as follows:

i) Input data: counts recorded by the detectors in the simulations with the geometry defined in the MCNP-X code and the variation in the internal diameter of the duct with 4-cm steps from 27 cm to 15 cm (D1, D2, D3, and D4).
ii) Output data: fouling thicknesses varying from 0 cm to 7 cm in steps

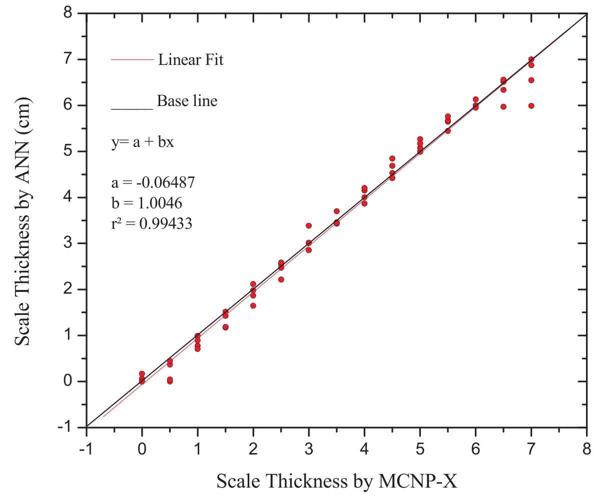

Fig. 6. Results obtained for the training and test sets.

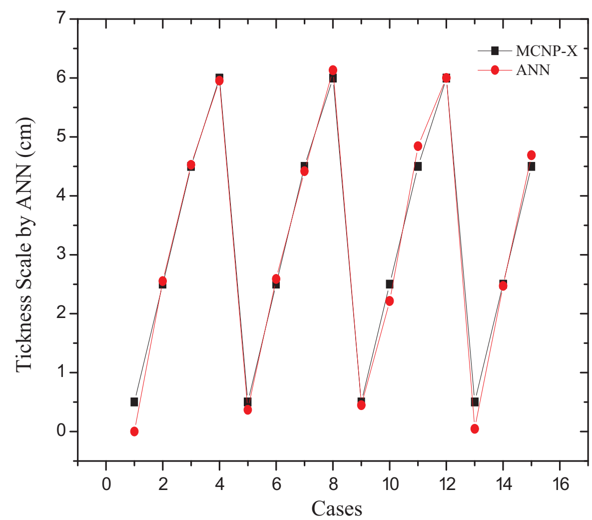

Fig. 7. Results obtained for the validation set.

Table 3
Data processed from ANN.

Relative error	Scale thickness
< 5%	56.667
5–10%	15
10–20%	10
20–30%	8.333
> 30%	3.333
r^2	0.9943

Table 2
Incrustation thicknesses (cm) obtained by the gamma transmission technique for nominal incrustations of 2 cm, 4 cm, and 6 cm.

	2 cm		**4 cm**		**6 cm**	
Height (cm)	**Scale thickness (cm)**	**Relative error (%)**	**Scale thickness (cm)**	**Relative error (%)**	**Scale thickness (cm)**	**Relative trror (%)**
3	1.99	− 0.71	3.98	− 0.56	5.96	− 0.65
3.5	1.99	− 0.73	3.98	− 0.60	5.97	− 0.55
4	1.99	− 0.64	3.98	− 0.51	5.97	− 0.57
4.5	1.99	− 0.56	3.99	− 0.36	5.97	− 0.48
5	1.99	− 0.57	3.99	− 0.24	5.98	− 0.26
5.5	1.99	− 0.44	4.00	0.10	6.01	0.09
6	1.99	− 0.47	4.00	0.06	6.04	0.70
6.5	1.99	− 0.49	4.00	0.06	6.09	1.46

of 0.5 cm.

Only the counts regarding photoelectric absorption were considered in this study, and the energy corresponding to this type of interaction was in channel 670. DAP was classified into 800 channels with 10 keV each.

4. Results

This section presents the steps to calculate the scale of barium sulphate thickness with analytical equations and processed data from the trained ANN to predict the scale thickness in different pipe diameters. Simulations were obtained with the MCNP-X code, using the tally card F8 for pulse height distribution estimation, and only the corresponding region of the photoelectric absorption was used. To ensure that the relative error associated with the counts of each detector was below 5% for all the cases, the calculation accounted to 1E7 NPS.

4.1. Scale thickness by analytical equations

The first data obtained were the values of the attenuation coefficient for all the materials that compose the studied pipe. For this, information such as density ($g\,cm^{-3}$) and mass fractions of iron pipe, barium sulphate scale, and oil was required as input data for the MCNP-X code for calculating the attenuation coefficient (Willian et al., 2006). Table 1 presents these coefficient values and their comparison with the theoretical data provided by the National Institute of Standards and Technology (NIST, 2010). These data were used for calculating the thickness of the scale.

Fig. 5 shows the thickness of the scale with a pencil beam source and a collimation aperture for crude oil, also varying the detection height and an initial nominal scale of 0.5 cm. By means of this study, the collimation aperture was defined with the lowest percentage relative error and adopted as the most adequate for the calculation of other scale thicknesses, with thicknesses varying from 2 cm to 6 cm.

The thickness of the scale is shown in Fig. 5, along with its respective percentage relative errors. It is possible to notice that the geometry using pencil beam source and 2-mm divergence presented the values closest to the theoretical value of 0.5 cm. In the other two cases, with divergence of 4.5 mm and 7 mm, the relative errors are relatively larger, maximum of 4.06%. This increase in the relative error in the last cases, where the beam angulation was extrapolated, demonstrates the importance of defining the geometry and the correct adjustment of the divergence.

In a second moment, the studies were carried out with variation in nominal scale of 2–6 cm, maintaining a divergence of 2 mm and the source pencil beam for comparative effect, because these data were those that presented smaller relative error. Fouling thickness data and the percentage relative errors obtained theoretically are presented in Table 2.

In all the cases, the fouling thicknesses were obtained with good detection sensitivity, with the thickness ranging from 0.5 to 6 cm. These cases presented relative errors lower than 1.46%, in the worst case.

4.2. Scale thickness by ANN training

Sixty cases were generated with the MCNP-X output files for neural network training, 36 cases for training, 16 cases for testing, and 8 cases for validation. For the network training, the input cases were inserted, in this case, the internal diameter of the duct and the counts in the detector, and the thickness of the inlay was the output data.

Fig. 6 shows the prediction of the scaling thickness by the ANN in comparison to the MCNP-X value.

It can be observed that the ANN can adequately predict the fouling thicknesses even when there is variation in the duct diameter and the thicknesses.

The correlation between the scaling thickness predicted by the ANN and the stipulated value for the learning set was calculated. The data were fitted to a linear equation by the least squares procedure; the slope of the line was 0.06487 and a linear correlation coefficient of 0.9943 was obtained.

The prediction for the test set is shown in Fig. 7, which indicates that RNA can adequately predict the thickness of barium sulphate. A good agreement is observed between the real scale thickness and that predicted by the ANN, showing its generalization capacity.

The good convergence of the ANN under the learning set was possible using the Perceptron Feedforward Multilayer Network, with backpropagation algorithm, in three layers where the stop criterion was the cross-validation with some activation functions, and the data processed are provided in Table 3.

After data processing, a good convergence of RNA can be observed, because more than 70% of the exiting data, that is, fouling thicknesses, present deviations up to 10% and a linear correlation coefficient (r^2) of 0.9943.

5. Conclusion

This work evaluated the detection geometry of a gamma transmission system and studied the influence of the opening of the divergence of a point source, the position of the detection system, source-detector type, and the composition of the damages and scales, with the aim of a repetition of a geometry that evaluated the impact of these parameters for the quantification of barium sulphate scale ($BaSO_4$) in oil pipes. The scale thicknesses were calculated using analytical equations, and computational simulation (MCNP-X) was used to generate cases for training and validating the ANN. The results of the calculation of the fouling thickness presented relative errors lower than 1.44%, showing good agreement between the values initially stipulated and obtained by simulations. A neural network was trained by varying the internal diameter of the pipe and the values of the fouling thickness. The processed data obtained deviations below 10% for 70% of the cases, with a correlation coefficient (r^2) of 0.9943. Test data for network validation, where the values of the actual fouling thickness were similar to those predicted by the ANN, demonstrate the generalization capacity and good convergence of the same; this indicates that this methodology can be used to predict the thickness of deposits in oil pipes.

Acknowledgments

The authors gratefully acknowledge the financial support from the Comissão Nacional de Energia Nuclear (CNEN) of Brazil. They also thank the Instituto de Engenharia Nuclear (IEN) of Brazil for the academic support.

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