Analysis of the transport of monoethylene glycol inside oil pipelines using numerical simulation and deep learning modeling

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Abstract. One of the challenges faced by oil production systems is the formation of inorganic scale. One of the methods employed to mitigate or prevent the damage caused by this phenomenon is the injection of inhibitors. The solvent used by many of these products is monoethylene glycol (MEG). To understand the influence of the injection of monoethylene glycol into an oil pipeline, this research investigates the behavior of the multiphase and multicomponent flow resulting from the injection of this solvent into a pipeline with oil and formation water, compared to the flow, under the same conditions, of only oil and formation water, through computational numerical simulation (CFD) and artificial neural network to describe the density of the formation water. It was possible to verify that the injection of monoethylene glycol, in an oil and formation water flow, led to changes in pressure, temperature, viscosity, density, and flow velocity. The average temperature of the flow was raised, the average pressure acquired a non-linear decreasing behavior, the average velocity changed at the injection point and the flow became less dense and more viscous.

Keywords: MEG, Oil, Formation Water, Numerical Simulation, Deep Learning

1 Introduction

Multiphase and multicomponent flows are those made up of two or more phases and components, either continuous or dispersed, with different physical properties, with the possibility of interconversion between the phases and diffusive flow of the components, in accordance with Krüger et al. [1]. These types of flows are present in a variety of situations, such as in the oil industry where there is a complex mixture made up predominantly of hydrocarbons and impurities such as inorganic salts, sand and water, accordingly Soares [2]. Inside production pipelines, the flow of this mixture is a highly complex phenomenon because, among other things, there is the possibility of inorganic scale, which is related to flow assurance problems, and is a historical challenge for this industry, accordingly Jordan et al. [3].

The ability to model this type of flow and predict the formation of inorganic scale is fundamental to develop strategies to combat the formation of scale because when this accumulation occurs in the producing well and

the pipelines it has a negative impact on production and can even lead to a total stoppage of production. As a strategy to combat scale formation, it is possible to use chemical anti-incrusting injection systems (scale inhibitor), where monoethylene glycol (C2H6O2 - MEG) is widely used as a solvent - a low-viscosity, odorless, relatively non-volatile, sweet liquid, completely miscible in various polar solvents and slightly soluble in some non-polar solvents, in accordance with Yue et al. [4]. Accurately monitoring the behavior of the products inside the pipelines is essential, as their incorrect use can accelerate or cause the recurrence of deposits and increase the damage caused by this, accordingly Kamal et al. [5].

In this research, the influence of the presence of monoethylene glycol (MEG), dosed as a solvent for scale inhibitors, in an oil pipeline was carried out using Computational Fluid Dynamics (CFD), together with the use of an artificial neural network to describe the density of the formation water as a function of the flow temperature, to obtain an efficient predictive methodology for the behavior of this flow.

2 Methodology

This section describes the activities carried out to model and perform, using the commercial software Ansys Fluent®. Two 3D numerical simulations in a laminar regime were performed. The first model refers to the two-phase flow of formation water and oil in an oil pipeline and the second the two-phase, multicomponent flow, resulting from the injection of MEG, dosed as a solvent for inorganic scale inhibitors, into the same pipeline as theof the first model to check the effect of the presence of monoethylene glycol on the flow velocity, absolute pressure, static temperature, density, and viscosity.

The *Volume of Fluid* (VOF) model, accordingly Ansys [6], was used to describe the multicomponent flow and the species transport model was used to describe the multicomponent flow. An artificial neural network *feedforward* was used to calculate the density of the formation water, using the *backpropagation* algorithm, in accordance with Silva et al. [7].

2.1 Multiphase model: *Volume of Fluid* (VOF)

The multiphase *Volume of Fluid* (VOF) model is an Eulerian approach that was developed by Hirt and Nichols [8] to solve problems with free boundaries, which are understood as surfaces on which there are discontinuities in one or more variables, such as interfaces between materials, fluids and deformable structures or shock waves. In this method, according to Ansys [6], the phases are treated as interpenetrating continua, the effects of the surface tension at the interface between the pairs of phases can be calculated and, where α_q as the volume fraction of the q_{th} phase and $0 \leq \alpha_q \leq 1$, we have:

$$\frac{1}{\rho}\left[\frac{\partial}{\partial t}(\alpha_q \rho_q) + \nabla \cdot (\alpha_q \rho_q \vec{v}_q) = S_{\alpha_q} + \sum_{p=1}^{n}(\dot{m}_{pq} - \dot{m}_{qp})\right]. \tag{1}$$

where S_{α_q} is the mass source term, $\dot{m}_{pq}$ is the mass transfer from the p phase to the q phase and $\dot{m}_{qp}$ is the mass transfer from the q phase to the p phase and $\vec{v}_q$ and ρ_q are the velocity and density of the q_{th} phase, respectively.

Likewise, only one momentum equation and one energy equation are solved for all fluids. Thus, for the linear momentum balance, we have:

$$\frac{\partial}{\partial t}(\rho\vec{v}) + \nabla \cdot (\rho\vec{v}\vec{v}) = -\nabla p + \nabla \cdot \left[\mu\left(\nabla\vec{v} + \nabla\vec{v}^T\right)\right] + \rho\vec{g} + \vec{F}. \tag{2}$$

where ρ is the density, $\vec{v}$ is the velocity, p is the pressure, μ is the viscosity, T is the temperature, $\vec{g}$ is the acceleration due to gravity and $\vec{F}$ is the body force and the energy equation is given by:

$$\frac{\partial}{\partial t}(\rho E) + \nabla \cdot (\vec{v}(\rho E + p)) = \nabla \cdot (k_{eff}\nabla T) + S_h. \tag{3}$$

where k_{eff} is the effective thermal conductivity, S_h is the volumetric heat source term, E is the energy, calculated as the mass-weighted average:

$$E = \frac{\sum_{q=1}^{n} \alpha_q \rho_q E_q}{\sum_{q=1}^{n} \alpha_q \rho_q}. \tag{4}$$

and E_q is the energy of each phase.

2.2 Multicomponent model: Species transport models

The species transport model describes multicomponent transport through convection-diffusion and can describe volumetric chemical reactions on walls, particle surfaces, porous regions, or model flows without these reactions occurring. In this model, the mass conservation equation, which is solved for $N-1$ species i in a mixture, where N is the number of species, can be written as Ansys [6]:

$$\frac{\partial(\rho Y_i)}{\partial t} + \nabla \cdot (\rho \vec{v} Y_i) = -\nabla \cdot J_i + R_i + S_i. \tag{5}$$

where $\vec{v}$ is the mass velocity, ρ is the density, R_i is a source term for the production of species i by chemical reaction, S_i is a user-defined source term, J_i is the diffusive flux of the species and Y_i is the mass fraction of the species i . For laminar flows, we have:

$$J_i = -\rho D_{i,m} \nabla Y_i - D_{T,i} \frac{\nabla T}{T}. \tag{6}$$

where $D_{i,m}$ is the mass diffusion coefficient of the species, T is the temperature, and $D_{T,i}$ is the thermal diffusion coefficient.

2.3 Artificial Neural Network (ANN)

An artificial neural network (ANN) is a type of machine learning algorithm in which internal parameters are modified according to sets of data provided, accordingly Farias [9]. In this work, an ANN model was used to describe the correlation of formation water density as a function of flow temperature, with the aim of not limiting the range of validity of the dependent variable. An artificial neural network feedforward was implemented, using the training algorithm backpropagation (Figure 1), with three input data (pressure [Pa], temperature [K], and salinity [mol/kg]), 13 hidden layers, 10 neurons per hidden layer, and output corresponding to the density of this water, in kg/m^3.

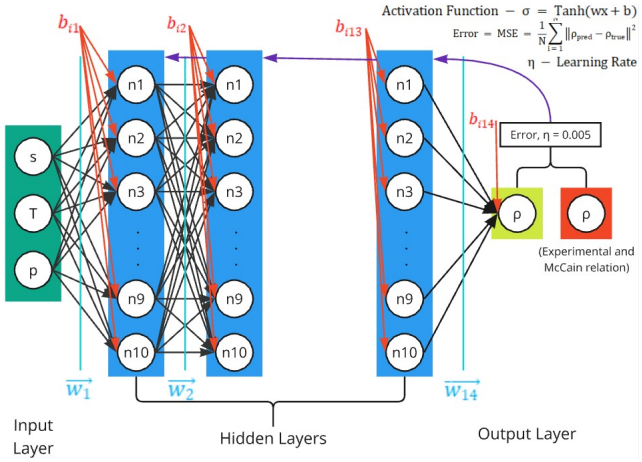

Figure 1. Neural network architecture

The hyperbolic tangent activation function was used, with the learning rate α= 0.005 and a database with 307 experimental data obtained from McCain [10], and 40,000 numerical data calculated from the McCain correlation, according to Mao and Duan [11], where w and S are the density and salinity of the formation water, respectively:

$$\rho_w = 62.368 + 0.438603S + 1.60074 \times 10^{-3}S^2. \tag{7}$$

From the database, a set of 28,215 data was randomly selected for training, a set of 6045 data was used for testing and a set of 6,047 data was used for validation. The model was trained in 330 iterations and the error was analyzed with the test set. The average absolute error obtained was 0.0006669522, indicating that the ANN model is capable of predicting density accurately. In the end, we used the network's prediction of density as a function of temperature, with salinity equal to 0.03764mol/kg, and pressure equal to 380kgf/cm^2 corresponding to the properties of the simulated formation water and a database temperature range between 24.59°C and 175°C.

Figure 2 shows the graphs of error in training and validation and of real values and predicted values of density.

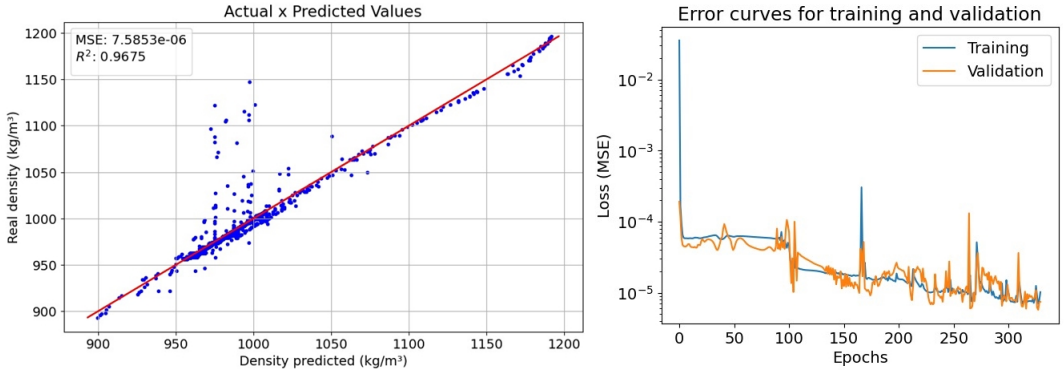

Figure 2. Density predicted and density test set and error curves

A root mean square error of 7.5853×10^{-6} and a coefficient of determination R^2 = 0.9675 were obtained, showing the efficiency of the predictive model.

2.4 Cases description

This analysis simulates the three-dimensional flow resulting from the injection of monoethylene glycol (MEG) into a 20m long stretch of pipe (located at a total distance of 275.5m away from the reservoir), in a pipeline of the oil production system (total distance of the pipeline: approximately 10km, from the reservoir to the Stationary Production Unit (SPU), as shown in Figure 3), and the flow of only oil and formation water in this same pipeline, to check the influence of the presence of MEG on the velocity, absolute pressure, static temperature, density and viscosity of the flow. The internal diameter of this pipeline is 0.12m and it is injected with MEG through a chemical injection valve (VIQ), which has an outlet diameter of $1.1 \cdot 10^{-2}$m.

The simulations were carried out in a laminar, transient regime, using the pressure-based solver and considering the aqueous phase as the primary phase and the oleic phase as the secondary phase. Boundary conditions were used:

CASE - OIL AND FORMING WATER:

Oil inlet - Location: Oil inlet (see Figure 3). We imposed a velocity of 2.21m/s, a temperature of 352.89K, and a volume fraction of the oil phase of 1.

Formation water inlet - Location: Formation water inlet (see Figure 3). Velocity equal to 2.21m/s, temperature equal to 352.89K, and oleic phase volume fraction equal to 0 were imposed.

Pipe outlet - Location: Outlet (see Figure 3). Temperature equal to 352.82K, and gauge pressure equal to 0 Pa.

Wall - Location: Wall (see Figure 3) temperature equal to 353.15K, stationary walls, and non-slip condition.

CASE - MEG INJECTION INTO PIPE TRANSPORTING OIL AND FORMATION WATER:

MEG inlet- Location: VIQ (see Figure 3). The injection velocity was 0.00693m/s, the temperature 353.15K, the MEG mass fraction 1, and the oleic phase volume fraction 0.

Oil inlet - Location: Oil inlet (see Figure 3). We imposed a velocity of 2.21m/s, a temperature of 352.89K, a mass fraction of MEG of 0, and a volume fraction of the oil phase of 1.

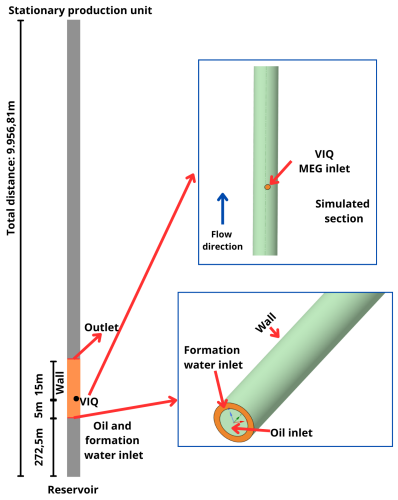

Figure 3. Illustration, out of scale, and location of the boundary conditions of the pipeline section

Formation water inlet - Location: Formation water inlet (see Figure 3). Temperature equal to 352.89K, velocity equal to 2.21m/s, MEG mass fraction equal to 0, and oleic phase volume fraction equal to 0 were imposed.

Pipe outlet - Location: Outlet (see Figure 3). Temperature equal to 352.82K, gauge pressure equal to 0 Pa, mass fraction of MEG backflow equal to 0.

Wall - Location: Wall (see Figure 3) temperature equal to 353.15K, stationary walls, non-slip, the diffusive flow of MEG equal to 0, diffusive flow of injection water equal to 0.

3 Results and discussion

Figure 4 shows the average density and viscosity of the two-phase and multicomponent flow of MEG injection into the pipeline with oil and formation water and the two-phase flow of oil and formation water in the same pipeline at different flow times.

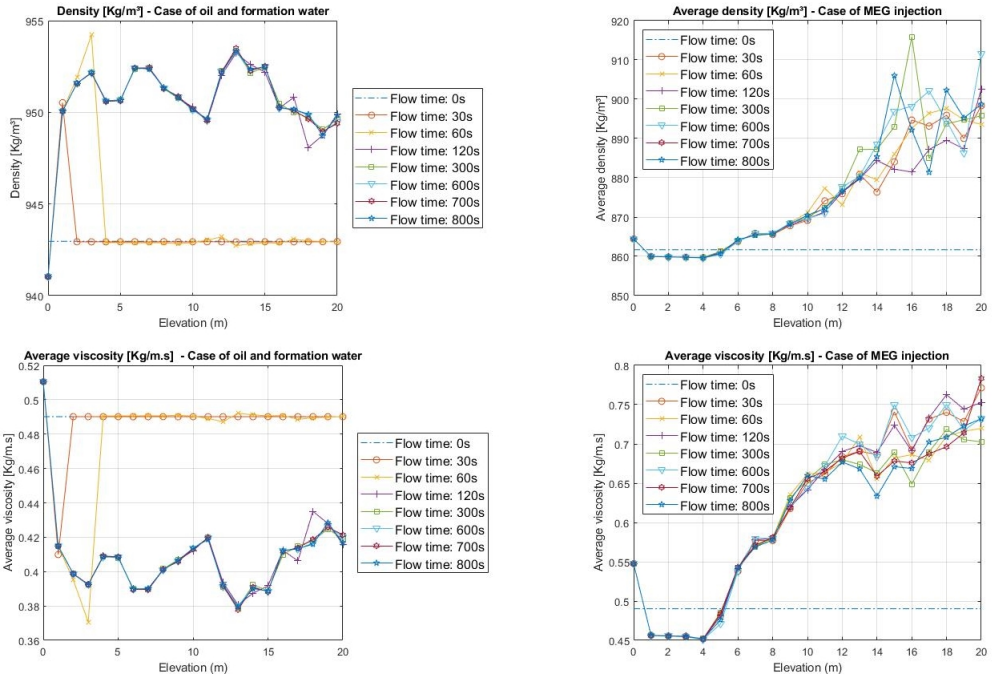

Figure 4. Average density and viscosity, in the case of oil and formation water and in the case of MEG injection

Analyzing Figure 4, it can be seen that the presence of monoethylene glycol altered the average density and viscosity of the flow. There is a decrease in density and an increase in viscosity. In the case of flow with only oil and formation water, the average density increases proportionally to the flow time, from y = 0m, while in the presence of MEG, there is an increase in density from the point of injection (y = 5m) and the average values always remain lower than in the aforementioned case.

Figure 5 shows the average absolute pressure, temperature, and velocity of the two-phase, multicomponent flow from the injection of MEG into the pipeline with oil and formation water and from the two-phase flow of oil and formation water in the same pipeline at different flow times.

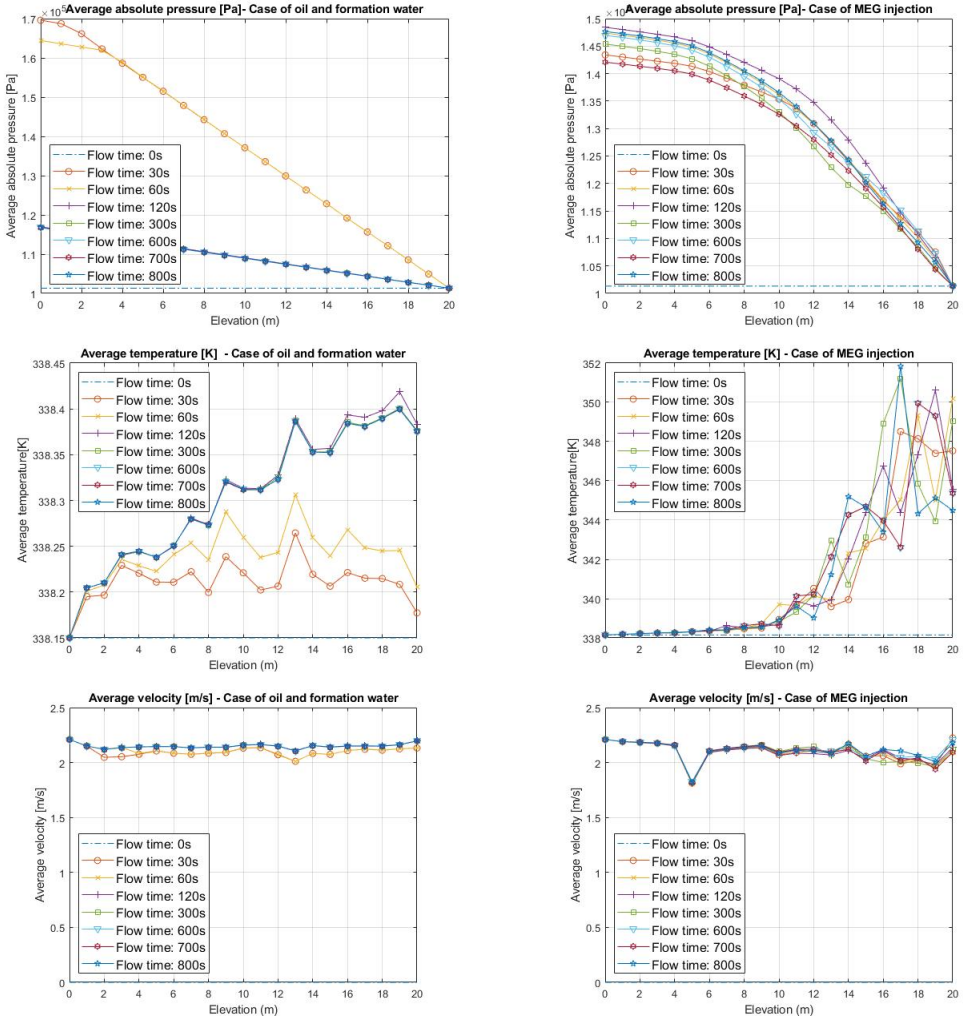

Figure 5. Average absolute pressure, temperature, and velocity, in the case of MEG injection and the case of oil and formation water

Figure 5 shows that the injection of MEG also led to changes in the absolute pressure, velocity, and average temperature of the flow. When only oil and formation water is flowing, the pressure rises at t = 30s and decreases in the following instants, with a linear behavior of the variable starting at y = 3 m, while with the presence of MEG, the absolute pressure decreases non-linearly. It can be seen that this injection increased the average temperature of the flow from y = 5m and led to a reduction in velocity at this same point, altering the flow pattern.

4 Conclusions

In this research, we proposed a numerical methodology for predicting the displacement of the scale inhibitor solvent monoethylene glycol in an oil and formation water flow, so as to allow professionals dedicated to flow assurance activities to verify the influence of the presence of this solvent on the conditions of oil production system pipelines.

It was possible to verify that this injection of monoethylene glycol, under the conditions simulated using computational fluid dynamics and an artificial neural network to describe the density of formation water, in an oil and formation water flow, leading to changes in pressure, temperature, viscosity, density, and flow velocity. The average temperature of the flow was raised, the average pressure acquired a non-linear decreasing behavior, the average velocity changed at the injection point and the flow became less dense and more viscous.

In the near future, we intend to simulate larger parts of the pipeline and carry out mesh convergence analyses and the use of dynamic mesh adaptivity methods, to improve the accuracy of predicting the displacement of monoethylene glycol in injection activities to inhibit scale in pipelines.

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References

[1] T. Krüger, H. Kusumaatmaja, A. Kuzmin, O. Shardt, G. Silva, and E. M. Viggen. Multiphase and multicomponent flows. *GRADUATE Texts in Physics*, vol. 41, n. 1, pp. 331–405, 2016.

[2] L. L. O. Soares. Determination of the start of paraffin deposition in oil production and transportation pipelines using multipoint temperature sensor (SMpT). *Dissertation (Master's) - Industrial Engineering Course, Federal University of Bahia*, 2017.

[3] M. Jordan, N. Feasey, and C. Johnston. Inorganic scale control within meg/methanol treated produced fluids. *SPE International Symposium on Oilfield Scale*, vol. 41, pp. 1–13, 2005.

[4] H. Yue, Y. Zhao, X. Ma, and J. Gong. Ethylene glycol: properties, synthesis, and applications. *Chemical Society Reviews*, vol. 41, n. 11, pp. 4089–438, 2012.

[5] M. S. Kamal, I. Hussein, M. Mahmoud, A. S. Sultan, and M. A. S. Saad. Oilfield scale formation and chemical removal: A review. *Journal of Petroleum Science and Engineering*, vol. 171, pp. 127–139, 2018.

[6] Ansys. Ansys fluent® theory guide, version 2023 R1. *ANSYS, Inc.*, 2023.

[7] I. N. Silva, D. H. Spalti, and R. A. Flauzino. *Redes Neurais Artificiais para engenharia e ciências aplicadas*. Universidade de São Paulo, São Paulo - SP, 2010.

[8] C. W. Hirt and B. D. Nichols. Volume of fluid (VOF) method for the dynamics of free boundaries. *Journal of Computational Physics*, vol. 39, pp. 201–225, 1981.

[9] T. S. Farias. Reversible neural networks and characterization of physical problems through differentiable programming. *Thesis (Doctorate) – Physical, Federal University of Santa Maria*, 2023.

[10] W. D. McCain. Reservoir-fluid property correlations-state of the art. *SPE Reservoir Engineering*, vol. 6, pp. 266–272, 1991.

[11] S. Mao and Z. Duan. The p,v,t,x properties of binary aqueous chloride solutions up to t = 573k and 100mpa. *The Journal of Chemical Thermodynamics*, vol. 40, pp. 1046–1063, 2008.