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Technical Paper

Adjustment of relative permeability curves parameters by supervised artificial neural networks

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Abstract

Relative permeability plays an important role in the characterization of multiphase flow in porous media. Such data are used as an input parameter for reservoir simulation models to determine the phase distribution, residual saturation, and predict the future performance of the reservoir. The inaccurate characterization of the relative permeability results in false representations of the velocity fields in the reservoir, inaccurate forecasts of production levels, and leads to wrong decisions, such as the incorrect selection of the well locations or the best recovery technique to be implemented. Besides, in simulations with a large number of data, as is the case of reservoirs with several grid blocks, the computational time for processing can last for several days. Given these difficulties, this work presents a methodology for forecasting relative permeability curves using feedforward artificial neural networks (ANNs) to improve simulation models in a short period of time. The input variables consisted of history data from production and injection wells and the analysis was based on the correlation between these data and relative permeability curves. Such methodology proved to be an alternative as a method of history matching, since the networks presented low error, with values very close or equal to the historical values, leading to a better production forecast with less computational demand.

Keywords: Artificial Neural Network. History Matching. Relative Permeability

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1. Introduction

Reservoir characterization is an essential process in the petroleum industry. It consists of modeling petrophysical characteristics of petroleum reservoirs such as rock properties, porosity, permeability, and saturation of fluids, and helps in more successful reservoir exploration, production, and management (Anifowose et al., 2013).

Since reservoirs consist of porous rocks filled with fluids that move through these pores, characterization of multi-phase fluid flow through porous media is particularly important (Liu et al., 2019). Therefore, the ability to correctly model relative permeability is considered the most valuable information required in reservoir simulation studies for predicting the performance of immiscible displacement processes (Al-Fattah & Al-Naim, 2009).

Estimates of relative permeability can be obtained from experimental measurement of core samples. These experimental determinations are laborious, expensive, and punctual since the core samples are difficult to obtain and represent a very small part of the whole reservoir. It also has limitations in measuring relative permeability of greatly low permeable cores and systems with extreme phase transformation and mass transfer as a result of pressure alteration (Al-Fattah & Al-Naim, 2009; Rostami et al., 2019). Relative permeability can be also obtained from both mathematical equations and empirical correlations derived from relative permeability curves. Based on experimental data, simplified models of relative permeability as a function of water saturation can be constructed.

Artificial neural network (ANN) technology has proved successful and useful in solving complex structured and nonlinear problems and has been widely used in the oil and gas sector to mimic the relationship between reservoir properties and designated outputs, such as flows (Al-Fattah & Al-Naim, 2009). Al-fattah and Al-naim (2009) developed an ANN model to predict relative permeability using experimental data from waterflood-core-tests samples collected from carbonate reservoirs of Saudi Arabia's oil fields where a genetic algorithm is used as part of the model-building process to identify the most relevant variables. However, according to the authors, the method is time-consuming, and it typically requires the construction and testing of thousands of networks, resulting in running the program for days.

Bagheripour (2014) presented an integrated method where a genetic algorithm is coupled with artificial neural network models to improve the accuracy of target prediction. The result of the committee machine can yield more precise results than the methods tested by the authors, although it is necessary for many steps leading to additional computation effort and time.

As can be seen also at Tahmasebi and Hezarkhani' work (2011), the computation time of a simulation run is an important factor and it can easily last several days or even several weeks, especially for a reservoir model that has multiple grid blocks, which is common among industry simulation practices. This study seeks, therefore, to develop a methodology based on ANNs capable of predicting the characteristics and representative relations of relative permeability curves using field production data and initial reservoir conditions with less computation effort as possible.

2. Methodology

This research was divided into two main steps. At first, we defined a methodology and the parameters of an artificial neural network to predict relative permeability in siliciclastic petroleum reservoirs. The second step consisted of applying and validating this methodology in a new scenario, where it is possible to predict future production.

2.1. Pre-processing

The definition of some parameters is crucial to obtain a good prediction result when using a neural network. The first ones to be stipulated are the number of layers and neurons per layer. To define these numbers, this research used at first a fixed time period for training and predict the relative permeability. So, if we train the network with ten time steps, it will predict the relative permeability and the production values only for ten time steps. This approach is simpler to perform and does not consider time as a variable.

At this research, the UNISIM-I benchmark provided by the Universidade Estadual de Campinas (Avansi, 2014) was used as a simulation model. It is based on the Namorado field, located in the Campos basin of the Brazilian coast, and has its cell scale defined to adequately reflect the reservoir's behavior, that is, its heterogeneities. Thus, a 100 x 100 x 8 m simulation grid was assumed, discretized into a grid corner point with 81 x 58 x 20 cells with 38,466 active cells. The UNISIM-1-H case study (Maschio et al., 2015) was used as a network input for training the relative permeability parameters. The model has 4 original producer wells, 10 producers inserted later, and 11 injectors also later inserted by the authors. It also contains the production history, with 4018 days of production and injection data, that was used to validate the proposed method.

2.1.1. Fixed time period simulation

Initially, 200 relative permeability curves for water and oil were generated based on randomly generated parameters, with means and standard deviations stipulated by the chosen benchmark. For the generation of these curves, the Brooks and Corey model was adopted to capture the shape of the relative permeability curves between two phases.

The following equations ((1, (2 and (3), are used to describe oil, water, and gas relative permeabilities, respectively, where $k_{rw,max}$ is the maximum relative water permeability, S_{wc}, the critical water saturation, S_{gc} the critical gas saturation, and n_o, n_w, and n_g the Corey exponents, which defines the shape of the permeability curves. These exponents can range from 1 to 6.

$$k_{ro} = k_{ro,max}\left(\frac{S_o - S_{or}}{1 - S_{or} - S_{wc} - S_{gc}}\right)^{n_o} \quad (1)$$

$$k_{rw} = k_{rw,max}\left(\frac{S_w - S_{wc}}{1 - S_{or} - S_{wc} - S_{gc}}\right)^{n_w} \quad (2)$$

$$k_{rg} = k_{rg,max}\left(\frac{S_g - S_{gc}}{1 - S_{or} - S_{wc} - S_{gc}}\right)^{n_g} \quad (3)$$

Such generated curves and the data of the UNISIM-I-H model were used as input to the reservoir black-oil simulator IMEX (CMG®) to obtain data of oil and water production, gas-oil ratio (RGO) and the bottom hole pressure (BHP) of the producers and injectors wells, in addition to the flow of water injected into injection wells.

The simulator outputs were then inserted as input into different supervised artificial neural networks. These networks have a feedforward architecture, sigmoid training function, and the update of the weights was carried out through a backpropagation model.

Each of the networks has different numbers of layers and neurons per layer, both generated randomly with the minimum number of internal layers being 1 and the maximum 5, and the number of neurons could range from 2 to 1000. The generation of random parameters allows no external influence or bias in the results, making the methodology applicable to any reservoir model.

After the generation of a network, it was trained and the results, that are the parameters that determine the relative permeability curve proposed by Brooks and Corey, in this case, the exponent n_w, $k_{rw_{max}}$, S_{wc} and S_{worw}, were compared with the relative permeability data generated randomly initially. Such validation was carried out utilizing the normalized mean square error (NMSE) (Equations 4 to 7). In the following equations, n is the number of samples (200), p_i the predicted results of each variable m (4) and d_i the real values.

$$NMSE = \frac{1}{n.MSEref}\sum_{i=1}^{n}(p_i - d_i)^2 \qquad (4)$$

where

$$MSEref = \frac{1}{m}\sum_{i=1}^{m} V_m \qquad (5)$$

the V_m is the variance calculated by

$$V_m = \frac{1}{n-1}\sum_{i=1}^{n}|p_{i,m} - \mu_m|^2 \qquad (6)$$

and μ_m is the mean of values

$$\mu_m = \frac{1}{n}\sum_{i=1}^{n} p_{i,m} \qquad (7)$$

Having a network presented NMSE less than 0.09, it was stored, and a new network was generated, trained, and validated until reached a total of twenty networks. After choosing the network characteristics, production history data were used to validate the applied methodology.

2.1.2. Variable time period simulation

In the initial test, it was necessary to define a fixed time period to train the network, and thus, it was only possible to define a relative permeability forecast for this period of time. In this new stage, once the network has been trained for an initial time period, it is possible to forecast the production over the whole productive time of the reservoir. The methodology also enables the retrain of the network to updated permeability data every time a new production data is obtained

To accomplish that, it was necessary to change the way the input data was organized. The input was divided by time period and it was considered the production and injection cumulative data instead of the absolute ones.

At this part of the methodology, another important parameter, the training function, was tested and defined. Three training functions were tested: Scaled Conjugate Gradient (SCG), Levenberg-Marquardt (LM), and Bayesian Regularization (BR).

2.2. Processing and validation

The definition of the ANN number of neurons and layers and the training function was the most important process to obtain a good prediction. Having these parameters been defined the processing and validation step was performed using also the NMSE, but now comparing all the posterior curves to the history data.

Subsequently, a sensibility analysis of methodology parameters was also performed to verify the minimal size of the ensemble needed to train the network and how well ahead the same ANN can be a good predictor of relative permeability.

3. Results and discussion

3.1. Fixed time period simulation

In Table 1, it is possible to verify the characteristics of the twenty networks that presented a NMSE less than 0.09, therefore, the most suitable prediction of relative permeability. Thus, the networks with the lowest error were 8, 14, 19, and 18 respectively. It is possible to verify that even smaller networks can generate good results, and the forecast error is not related to the number of neurons, if there is at least a minimum number.

It is also possible to notice that there is a minimum of 174 neurons if there is only one layer, or more layers if the number of neurons is less than 100. This shows that these parameters are the basic necessities for this analysis since lowest numbers had NMSE higher than 0.09.

Table 1- Characteristics of the generated ANNs and their errors after training.

ANN	Number of neurons per layer	NMSE	ANN	Number of neurons per layer	NMSE
1	[323 246 130 199]	0.0790	11	[297 475 315 260]	0.0737
2	[203 50 152]	0.0746	12	[340 250]	0.0692
3	[196 248 81 470 449]	0.0881	13	[241 443 53 215]	0.0795
4	[321 273 498 233 371]	0.0722	14	[355 22]	0.0436
5	[393 120]	0.0884	15	[366 230 274 247]	0.0704
6	[300 449 343 331 16]	0.0833	16	[187 309 378 57]	0.0736
7	174	0.0814	17	[368 103 169 476 102]	0.0799
8	[365 343 122 141 352]	0.0395	18	[102 351 219 306 125]	0.0569
9	[237 336 467 401 41]	0.0852	19	[461 359 55 79]	0.0513
10	[63 51 422 495 27]	0.0873	20	[209 74 135 11 256]	0.0842

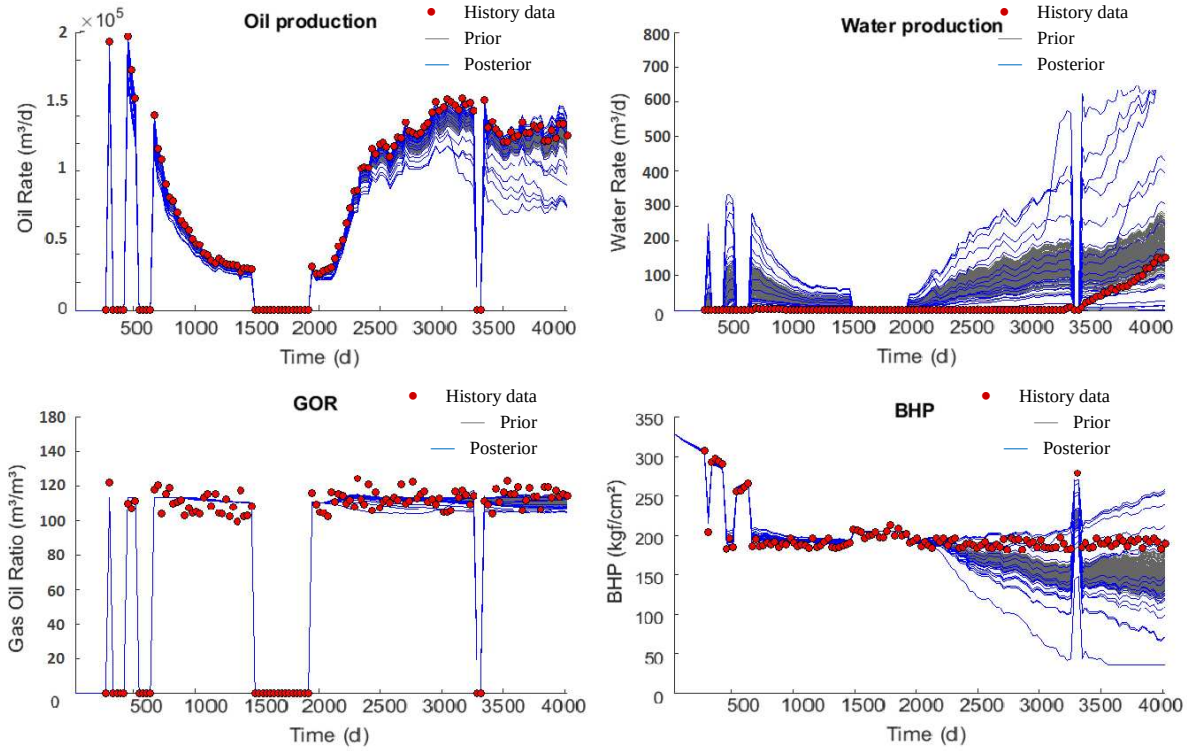
Source: produced by the author.

With the definition of the best number of neurons and layers, and defining the standard and fastest training function, that is, the Scaled Conjugate Gradient (SCG) we performed the initial methodology to see its applicability. To validate the result, curves of oil and water production, RGO and BHP were generated for a producing well and water injection and BHP curves were generated for an injector well, and all of them were compared to the history data and the ones used in the training process.

In the figure below (

Figure 1), the predicted curves after training are in blue, before training, in gray, and the history values are marked by red dots.

Figure 1- Predicted curves for producer well three with a fixed time period in blue, training curves, in gray, and history values in red dots.



Source: produced by the author.

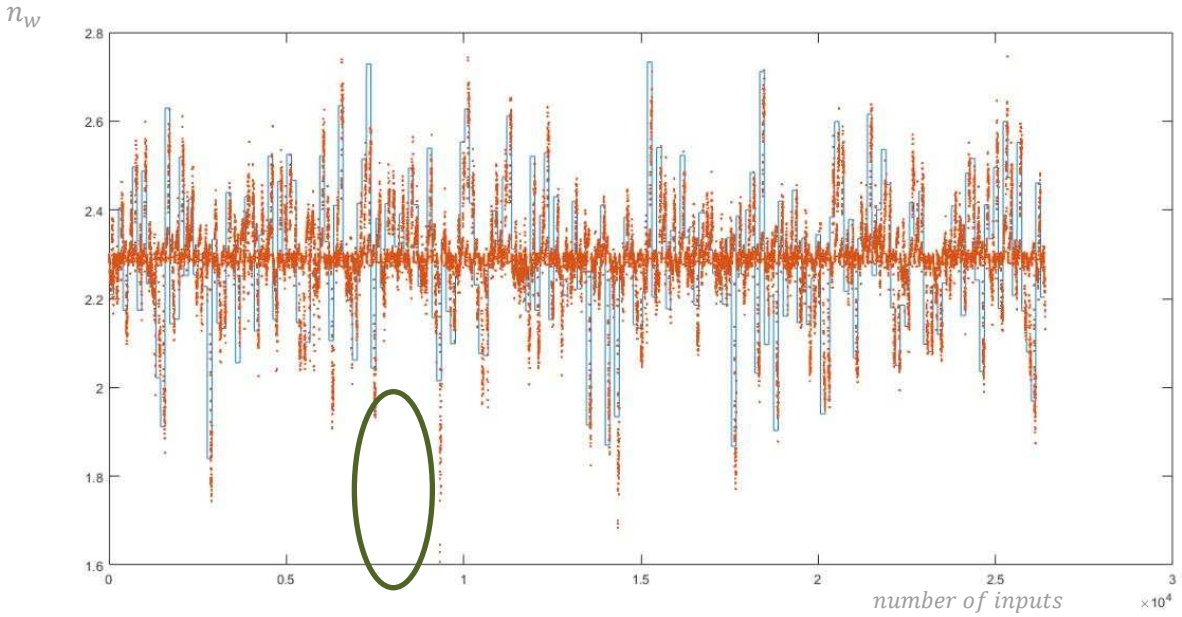
Since the objective of the adjustment is to improve the simulation model seeking to approximate the predicted values to the historical values, there was an improvement in the prediction. Some networks have a low error prediction, with values very close to or equal to the historical values, while others present very different results. To reduce the forecast errors, it is necessary to create a filter to eliminate such disparate networks and the adjustment of other network parameters as the training function that was analyzed later.

From these results, it was possible to verify the applicability of neural networks in problems of history matching, although this first methodology did not apply to real problems since it was only possible to predict a fixed period of time and there are networks with high error values. For this reason, a new configuration of input parameters was adopted, now using the time as an input, so that it was possible to train the ANN with a short time period and predict relative permeability values, as we obtained new data along with the productive life of the field.

3.2. Variable time period simulation

Using this new input configuration, three training functions were testes: Scaled Conjugate Gradient (SCG), Levenberg-Marquardt (LM), and Bayesian Regularization (BR). The SCG is faster and requires less memory since the training process stops when the mean squared error of the validation samples stops increasing. However, as can be seen in Figure 2, where the blue lines are the n_w values used as the ANN input and the orange dots are the ones predicted, this results in an inadequate adjustment for complex problems, such as the one we are dealing with. Both the Levenberg-Marquardt and Bayesian Regularization algorithms showed better fitting results.

Figure 2- Comparison between the input data (blue line) and the predicted data after the training process using SCG (orange dots). Detached in green, is an example of outliers.



Source: produced by the author.

The LM algorithm also stops the training process when the mean squared error of the validation samples stops increasing, but its algorithm is more complex since it varies the parameter updates between the gradient descent update and the Gauss-Newton update. A more detailed description of both algorithms and their differences can be found at BAFITLHILE, LI, and LI (2018) research. The LM training process usually requires more memory but less time than the BR since it stops the training process according to adaptive weight minimization (regularization).

Table 2 shows the mean time spent on training using the three training functions described above and the NMSE obtained with a comparison between the predicted values and the actual values.

Table 2 – Errors and mean time spent training on three training functions.

Training function	Time spent to train	NMSE
Scaled Conjugate Gradient	1,524 seconds	0.1627
Levenberg-Maquardt	10,874 seconds	0.1359
Bayesian Regularization	16,039 seconds	0.1652

Source: produced by the author.

As the training error of the LM algorithm was lower than BR and the time spent in the training process is also lower than BR, we chose to use the LM algorithm as training function.

The next step was to observe the minimum number of models needed to train the network. The tests were made with 100, 200, 500, and 1000 models, randomly generated with the LM algorithm. Table 3 shows the errors (NMSE) of the four sizes of training data and the time spent in the training process.

Table 3 – Time spent and error of four sizes of training data.

Size of the training data	Time spent to train	NMSE
100	1,524 seconds	0.1404
200	4,132 seconds	0.1652
500	10,874 seconds	0.1359
1000	124,567 seconds	0.1311

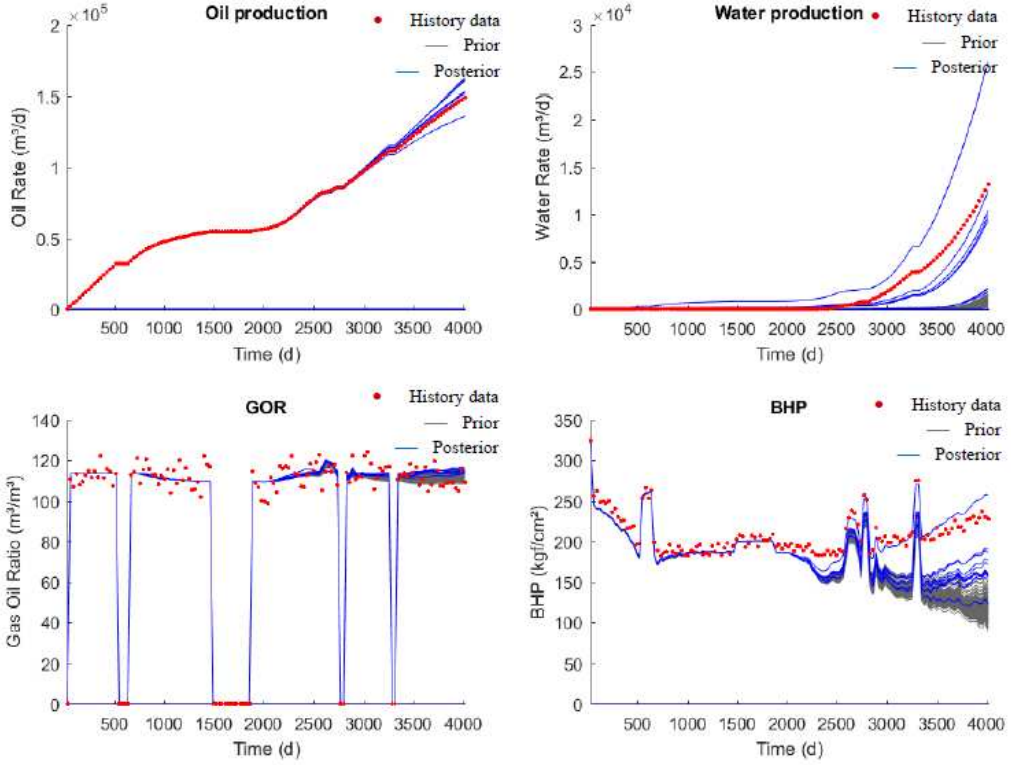
Source: produced by the author.

The smallest error was obtained, as expected, using 1,000 models to train the network. However, it took over 34 hours to train and the NMSE was only slightly better than using 500 models. Also, the NMSE of 100 models was smaller than the one with 200 models, yet, when we plotted the forecast and the training data, it was possible to see that the predicted data had low variance, that is, they were always the same and it has not changed for each case. Therefore, we decided to adopt 500 models as ideal for training the networks created from now on.

With all the parameters stipulated, that is, 500 randomly generated curves used to train a [50 100] neural network, with the LM training function, the complete methodology was performed. The results of two production wells and one injection well are shown in Figure 3, Source: produced by the author.

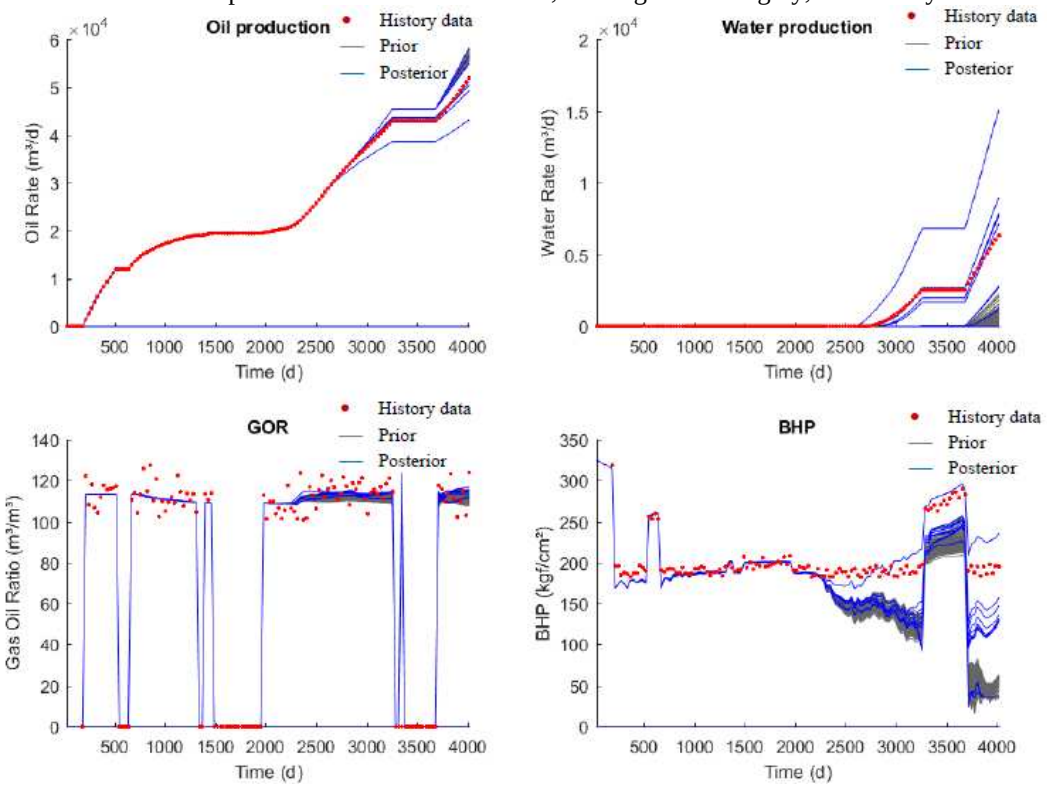
Figure 4, and Figure 5, respectively. The final curves, after applying the ANN, are in blue, the ones simulated used in training, in gray, and the history values are marked by red dots.

Figure 3- Predicted curves for producer well one in blue, training curves in gray, and history values in red dots.



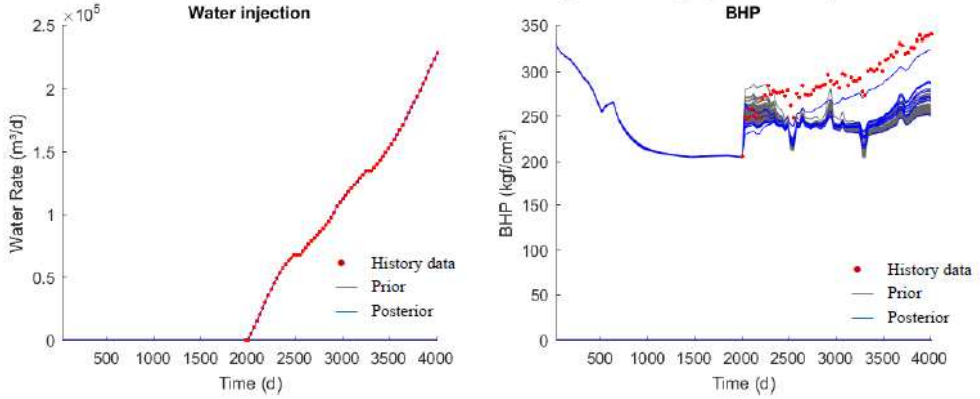
Source: produced by the author.

Figure 4- Predicted curves for producer well fourteen in blue, training curves in gray, and history values in red dots.



Source: produced by the author.

Figure 5 - Predicted curves for injector well seven in blue, training curves in gray, and history values in red dots.



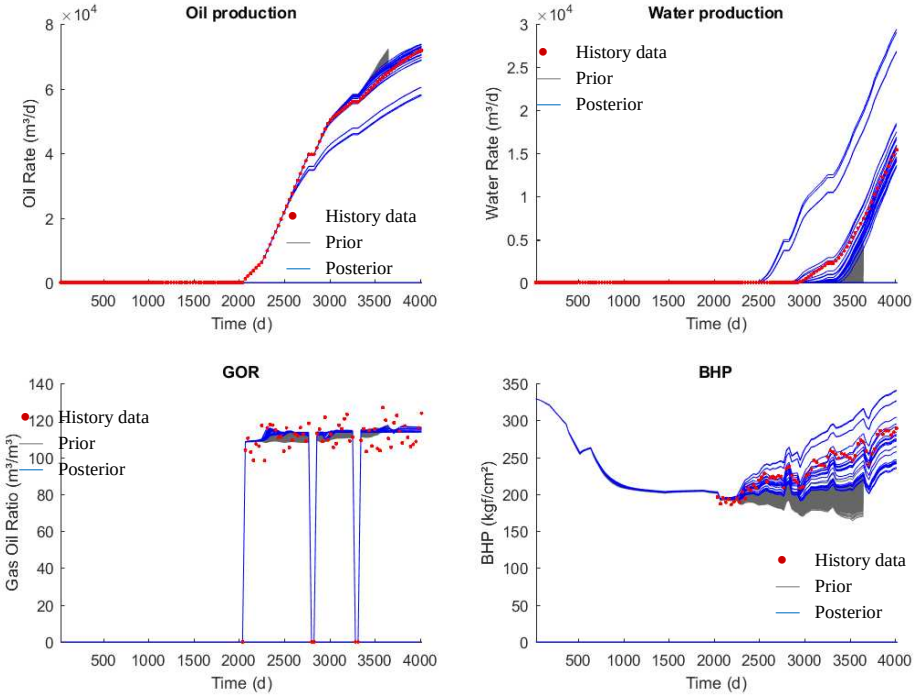
Source: produced by the author.

It is possible to notice, especially in the water production and BHP graphs, a relevant improvement in the forecast, with the predicted values (blue lines) being much closer to the historical data (red dots) than the simulation results before the ANN utilization (grey lines), both for producing and for injectors wells. Some curves still underestimated or overestimated the productions, this is because none of the historical values was used to refine the results. To improve the prediction a filter can be applied to reduce data dispersion and, for future work, the methodology can be performed iteratively by using the new prediction to retrain the network continually reducing the error.

The figures below (Figure 6 and Figure 7) were obtained by training the ANN with only 120 time steps and the production was estimated for one year ahead. We can see that the results are as good as

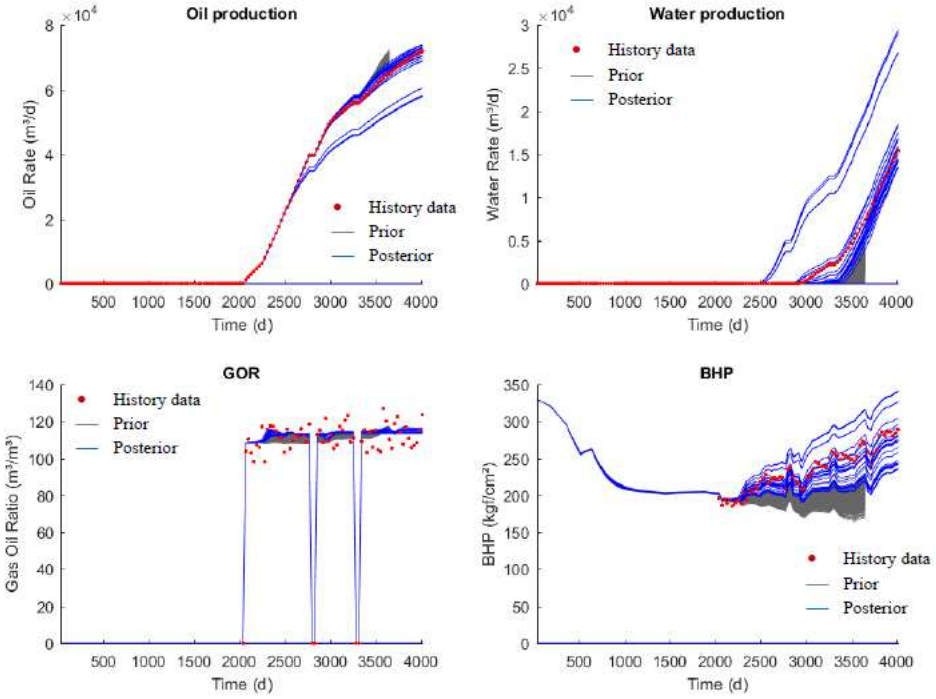
the ones obtained before, with a mean error of the predicted production of 18%, evidencing the network's potential to predict future production based on history data.

Figure 6 - Predicted curves for injector well four in blue, training curves with 120 time steps in gray, and history values in red dots.



Source: produced by the author.

Figure 7- Predicted curves for injector well four in blue, training curves with 120 time steps in gray, and history values in red dots.



Source: produced by the author.

4. Final considerations

In this research, a routine was developed to determine the relative water permeability curve, using a feedforward artificial neural network modeling for the oil reservoir proposed. The ANN model was validated from historical production data and the results obtained showed an improvement in the prediction of relative permeability data, with the error decreasing by about 20%. The time spent on forecasting has also decreased from a couple of days to approximately 10 hours, showing that the proposed methodology is faster than typical historical correspondence techniques without losing accuracy.

Also, the adjustment of relative permeability through history matching is an inverse problem that is badly placed, so several curves can be a solution to the proposed problem. Since the proposed methodology can generate a large number of possible solutions by adding noise to the network inputs, it is possible to find different curves that best suit the model in a short period of time.

For future work, the authors will focus on modifying the input data to make it easier to apply it for different time steps and on implementing a filter together with an iterative methodology to reduce data dispersion.

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