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Application of Artificial Intelligence in Flow Assurance

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Abstract
Artificial intelligence has evolved in automation. Supervision of process plants is one area where this evolution has resulted in significant gains. In this article we present the development of an algorithm for the supervision of producing wells. It is shown how AI is capable of improving operations by executing predictive assessment of production units, improving the quality of supervision and reducing downtime.

Keywords
AI, machine learning, optimization

Introduction
Oil companies have been looking for different alternatives to increase their oil recovery. In this scenario, optimizing operations is crucial. Artificial intelligence algorithms are under constant development but so far, few actual applications with significant gains have been reported. In this article we present the development of an algorithm that has been applied and has generated significant information for operational support.

Methodology

The AI algorithm is able to estimate the flowrate of individual wells, establishes targets for bottom hole pressures and through optimization algorithms determine optimal gas lift flow rate.
Initially it executes preprocessing of real time operational data (from Plant Information PI). It then executes simulations in different software (HYSYS, PIPESIM, OLGA) to generate relevant engineering information for its AI algorithm. Statistical analyses are done to further adjust important operational parameters, such the gas lift flow rate.
The algorithm uses different sources, as illustrated in figure 1. The offshore oil production can be represented by the combination of fluid properties, topside simulations, real data acquisition and flow assurance simulations.
Each of these fields has some parts that can be substituted for a surrogate model, in some cases these models are represented as neural networks that are trained with real data and present outputs that correspond to the expected values, without need to develop a complex and phenomenological model.

Surrogate modeling or data driven modeling are themes increasingly encountered in the literature (Bhosekar and Ierapetritou, 2018), for example these kinds of models already have been used to analyze multiphase flow (Seong et al, 2020). Specifically, the artificial neural networks have been used in this work and it’s widely used throughout the different disciplines of chemical and process engineering (Cavalcanti, 2021).

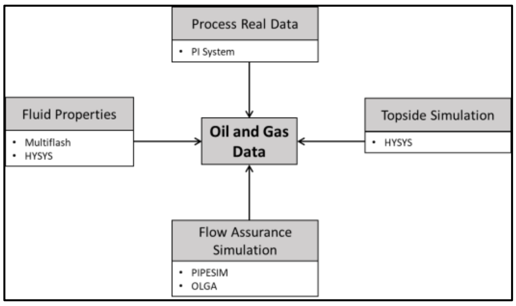


Figure 1: data scheme.

Computational Procedure

There are different operations that are executed in this routine. It will be described two of them, the field data acquisition and pos processing and the surrogate models modeling.
For the data acquisition there have been developed a python script to acquire data from the PI webservice API all day long. As these data are raw and often present a lot of noisy, they need a pos processing to improve the visualization and the implementation different data analysis techniques.

For the artificial neural network generation well tests results and PIPESIM simulations are used to generate a huge number of samples with different operational scenarios, varying the boundary conditions for different wells (arrival pressure, gas lift rate, inlet temperature, etc). These data are then used to train a neural network, that is tested and used in optimization routines.

Results and Discussion

In the Figure 2 there are presented a real time data acquisition that present the processed values of gas lift flow for different wells, improving the visibility of the data and allowing to detect rapid changes with time derivatives calculations, which is not possible to implement in the raw data because it presents a lot of oscillations.

Different combinations of input and output variables could be analyzed to generate the artificial neural network, the general model could be developed with the following architecture:

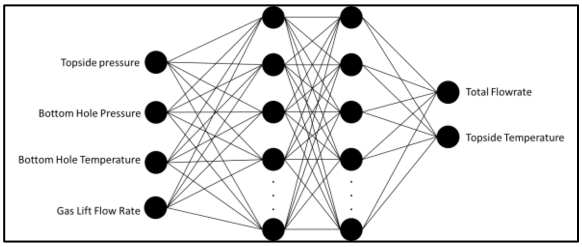


Figure 2: architecture of one of the neural networks developed.

The neural network has been developed with two hidden layers, specifying the following variables as input and outputs (could be any combination of them)

Input variables:

- Gas lift flowrate
- Bottom hole pressure
- Topside pressure
- Bottom hole temperature

Output variables were:

- Flowrate
- Topside Temperature

The following figure shows the estimates of the flow given by the trained neural network for a flowline compared to the expected data from a commercial software simulation.

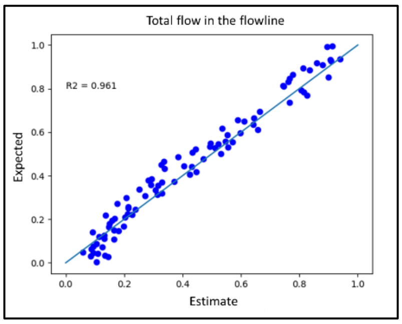


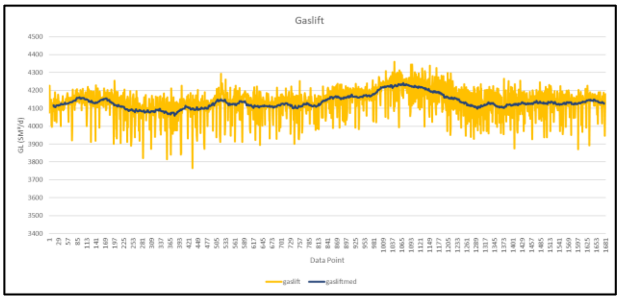
Figure 3: results of one of the trained neural networks.

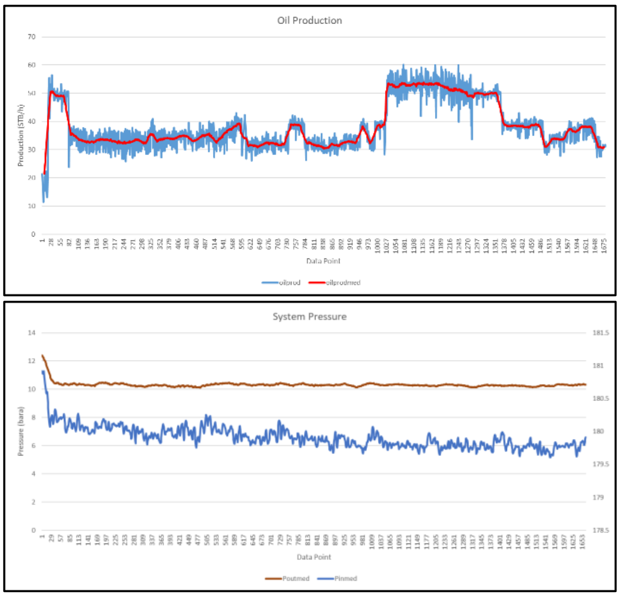
All these calculations and data were done inside a unique ambient that shares all these data. The algorithm was capable of estimating the flowrate of individual wells, calculating the optimum gas lift injection, and improving the data visualization and interpretation.

The Oil and Gas Data algorithm has been used to help optimize oil and gas production. With each well being modeled with a surrogate model that gives the oil flow as the output, an optimization algorithm has been developed to increase the total oil production, reaching the optimum gas lift injection for each well with the maximization of the total production as the objective function.

In this practical example, the system variables for a single well were used to calibrate a PIPESIM model of the well, and the model was used to generate data.

The data collected from the well underwent some processing, in order to remove outlier records that could offput the model. As the measurements from real instruments registered through the PI system contain some degree of noise, there was also a step of smoothing over the data, using a Rolling Average Technique so that the neural network could better read the system variables. Processed data and Rolling Average application can be seen in the graphs below.





Figures 4-6: data input for model calibration.

This generated data was then used to train the neural network, resulting in a model capable of predicting the well production with new conditions for that well. The data was selected from an appropriate section of the data, consisting of data points 350-500. The resulting neural network contains two layers with a hidden size of 160 nodes, a learning rate of 2E-3 and uses ReLU as the activation function. The results can be seen below, with the comparison of the expected values taken from the well, and the estimated values from the neural network.

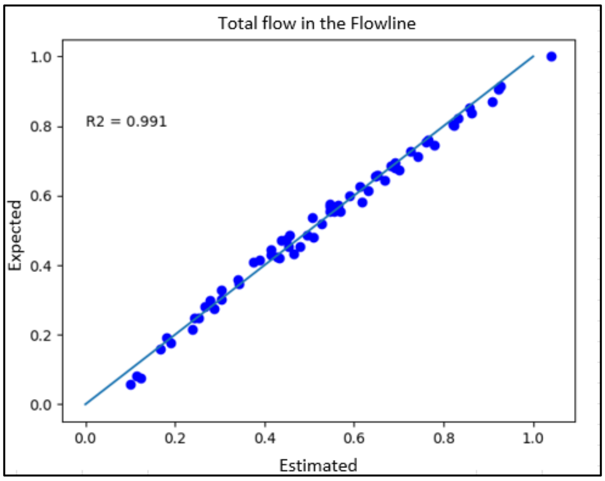


Figure 7: results of the neural network.

Having completed the neural network adjustments to the well, we may use it to estimate better production conditions, for instance the optimal gaslift injection quantity for the specific well. The following graph was constructed with the application of the neural network, and it can be used to ascertain that a better production may be reached if the gaslift injection is reduced.

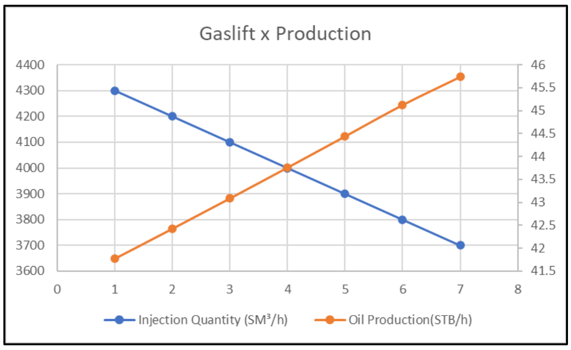


Figure 8: neural network application.

Conclusions

Surrogate models were used to represent the flow and process conditions. The results were used for training a neural network.
The algorithm has been able to determine optimal gas lift flow rate and individual well flowrate, proving it can be used to increase production variables.
The application of this strategy can be expanded to other parts of the oil production unit. Data acquisition and pre-processing has shown to be fundamental to guarantee the quality of the algorithm.

Acknowledgments

Responsibility Notice

References

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