Enhancing GOR Estimation in Gas-lift Oil Production: A Comparative Study of Support Vector Machines and Neural Networks ⋆

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Abstract: The accurate prediction of GOR (Gas-Oil Ratio) in oil production operations is crucial for optimizing production and ensuring the longevity of oil wells. In this study, we compare the performance of SVR and Neural Networks for predicting GOR in oil wells operating with gas lift elevation production. Our results show that neural networks outperform SVRs in terms of accuracy and speed, making them a more suitable approach for these predictions. To validate our findings, we collected and analyzed data from real-world oil wells, using both SVR and neural networks to make predictions. We found that the neural network approach was able to accurately predict GOR within a reasonable timeframe, whereas the SVR approach was slower and produced less accurate results. Our study provides valuable insights for oil well operators and engineers seeking to optimize their GOR predictions.

Keywords: Identification, Neural Networks, Machine Learning, Oil and Gas Production.

1. INTRODUCTION

Oil wells are complex systems that, while being very economically important, are very hard to accurately model due to uncertainties associated with the process of oil extraction. In oil production, there are many variables susceptible to uncertainties that are important to assess the performance and behavior of the well. These uncertainties derive from that they are specifically related to reservoir variables, which are hard to measure and accurately model (Jahn et al., 2008). For instance, there are many fluid elevation mechanisms to help so called brown wells (Jahn et al., 2008). One such techniques is the Gas-lift, which is widely used in the oil and gas industry. In a gas-lift elevation system, gas is injected into above the production packer, to reduce the hydrostatic pressure and improve the flow of oil to the surface. Predicting the amount of gas needed for optimal gas-lift performance is one of the many challenging tasks involving production, as it requires taking into account various factors such as reservoir characteristics, fluid properties, and production rates, many of which being either uncertain or hard to model. Example of important variables related to production are the gas-oil ratio (GOR) and the basic sediments and water (BSW), which are essentially measures of gas and water inside the production fluid Jahn et al. (2008).

GOR is a measure of the amount of gas that is produced in relation to the amount of oil from the reservoir. The measure can be expressed either as a mass ratio between gas and oil, or a volumetric ratio, which is the one considered for this work. Meanwhile, BSW is a quantification of the impurities present in the oil extracted from a well. It accounts for the combined volume of solids and water within a specified volume of crude oil. BSW serves as a vital parameter in oil production because it influences both the quality of the produced oil and its actual weight. Both GOR and BSW are important parameters when concerning evaluating well production performance and calculating optimization. However, since physically both parameters are entirely dependent on reservoir fluid properties, many uncertainties are associated with any physical model that might include them (Jahn et al., 2008). This opens the possibility for using data-driven black-box modeling (or, in other words, machine learning tools) to estimate the GOR and BSW. Machine Learning tools are powerful in the sense that accurate models can be obtainded only from input-to-output data (Bishop, 2006). There are other instances of static black-box models being applied in oil and gas industry related problems, such as Thanh et al. (2020), where a neural network is used to predict CO2 recovery. Another instance is Junior and Moreno (2019), where, among other tools, a Support Vector Regression (SVR) model is employed to calculate the bottom-hole pressure based on the GOR. For this work, we employ a model which separately identifies the GOR and BSW based on the production well pressures and gas-lift injec-

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tion, which is almost as developed in Junior and Moreno (2019), but reversed.

One of many problems involving oil and gas related plants such as an oil well, is that field data tend to be either scarce or unavailable. One solution for this type of issue in physical plants is already present in the literature in the form of Physics informed machine learning (Karniadakis et al., 2021). The three main fronts of physics informed machine learning are data augmentation through simulated data, utilizing models with structure based on the system physics, and applying regularization through the physical equation residue. Our approach in this work is to generate data from an oil well simulated in the MARLIM software, and train the model based on the resulting data, to apply it on the real counterpart of the MARLIM model Seman et al. (2020). One can say this approach belongs to the data augmentation approach of physics informed machine learning.

The objective of this study is to improve BSW and GOR estimation in gas-lifted oil wells. We test and compare the performance of two different models: SVR and Neural Networks (NN). Although the neural networks are more complex, they outperform SVR when sufficient data is available, through complexity alone (Bishop, 2006). We first trained both models using the MARLIM simulation, and used real-world data as test data for the prediction of both GOR and BSW, obtaining an outstanding performance in both models.

The contributions of this work goes twofold:

- Obtaining models from machine learning (namely, SVR and NNs) to predict GOR from readily availabe well data, being able to provide a method to easily infer these parameters.
- Testing and Validating the approach of inserting simulated data into training to perform in the real world counterpart of the same well.

The work is distributed as follows: Section 2 describes the oil production process, Section 3 describes the SVR and NN models, Section 4 describes the experiments, and Section 5 concludes the work.

2. BACKGROUND AND CONTEXT

A oil well referes to the tubulation responsible for extracting the oil from the reservoir and placing it into the surface. Figure 1 is a schematic representation of a gas-lifted oil well. In this case, the production tubing is at the center, while the gas for the gas-lift production is provided from an annulus around it. For the purpose of this work, we are concerned with obtaining the GOR and BSW of a given well, which are measures related to the fluid that is entering the well from the reservoir. There are many ways for a well model to represent the fluid being produced, with the simplest being considering the oil production a linear relation of the well bottom-hole pressure P_{bh} (which is also referred to as the pressure measured at the Permanent Downhole Gauge (PDG)), and the pressure at the reservoir P_r:

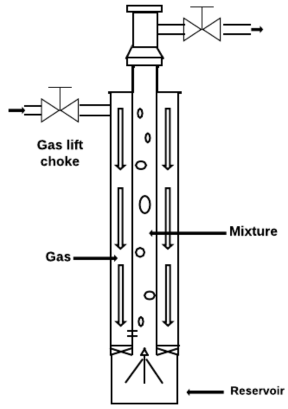

Figure 1. Schematic of a gas-lifted oil well.

$$\omega_{o,r} = PI(P_r - P_{bh}) \quad (1)$$
$$\omega_{g,r} = GOR\omega_{o,r} \quad (2)$$
$$\omega_{w,r} = \frac{BSW}{1 - BSW}\omega_{o,r} \quad (3)$$

where $\omega_{o,r}$ is the oil mass flow from the reservoir, $\omega_{g,r}$ is the mass gas flow from the reservoir, and $\omega_{w.r}$ the water mass flow from the reservoir. PI, the productivity index, BSW and GOR are three important variables to measure the performance of a given oil well (Jahn et al., 2008). Given these equations, we can easily obtain GOR and BSW from the flows alone, however flows tend not to be easy to directly measure in oil wells, hence the need to develop a model from indirect measures instead. We can consider the reservoir production equations as a basis to stipulate a function mapping for the calculation of both GOR and BSW, based on models such as the ones derived by Jahanshahi et al. (2012), which is:

$$GOR = f(\omega_{g,gs}, P_r, P_{bh}, P_{wh}, PI, ...) \quad (4)$$
$$BSW = g(P_r, P_{bh}, P_{wh}, PI, ...) \quad (5)$$

where $\omega_{g,gs}$ is the gas-lift source flow, and P_{wh} is the wellhead pressure. In production well systems, the bottom-hole pressure has a certain degree of dependence on the wellhead pressure, which is the reason the wellhead variables are present as inputs in this mapping. Also, other inputs are accepted, was Eqn. (1) to Eqn. (2) represent a simplied version of the flow dynamics. f and g could be physically modeled, however since well production models are very prone to uncertainty, we experiment the viability of data-driven approaches instead, by gathering data simulated from the steady state MARLIM model on a real well owned by Petrobras.

There is a limited number of scientific articles specifically addressing the prediction/estimation of GOR and BSW. One example for GOR estimation is Hashemi Fath et al. (2020), where a MLP neural network is used to estimate solution GOR, with the diference being that the data is obtained from data obtained from analyzing the fluid. However, similarities can be found in other oil well process predictions, such as Virtual Flow Metering (VFM) (Bikmukhametov and Jäschke, 2020) and various oil flow processes. In these related fields, regression-based models have often been demonstrated to be less accurate than

Neural Networks (NNs). For instance, this is evident in AL-Qutami et al. (2018) and Sandnes et al. (2021). In these articles, NNs were compared not to Support Vector Regression (SVR) but rather to Gradient Boosted Trees. In summary, this work uses data-driven methodology to try to predict and estimate GOR and BSW instead of flow, as in VFM.

3. MODELING

In this section, we will discuss the modeling techniques employed in our study to predict BSW and GOR in oil rigs. We will explore the use of Support Vector Machines (SVR) and Convolutional Neural Networks (CNN) as our primary approaches. We will provide a detailed overview of each method, including their mathematical foundations, parameter tuning, and model selection.

3.1 Support Vector Machine (SVR)

This section will cover a background on how SVR-based estimation was done. It will also deal with some theories and methods used to estimate the GOR and BSW parameters.

SVR (Jordan et al., 1997) is a regression algorithm based on SVM regression algorithm that relies on SVM, which is a machine learning algorithm for classification problems (Vapnik, 1995). SVM implements minimizing the fit error and reducing the upper bound of the generalization error at the same time, making it increase the generalization ability of the model (Ko and Lee, 2013). The SVR algorithm uses a nonlinear kernel and support vectors of the input data selected from the training stage of the algorithm. In this way, SVR combines the current inputs of the algorithm with the support vectors and the nonlinear kernel to be able to find the current estimation of the output variable.

A support vector algorithm for regression known as ϵ-SV Regression has been proposed. A training data set is defined $\{(x_1,\ y_1),\ .\ .\ .\ ,(x_l,\ y_l)\} \subset \chi \times \mathrm{R}$, in which χ represents the input space. The goal of the algorithm is to find a function $F(x)$ that has a maximum deviation ϵ from the targets y_i for all training data $(i = 1, 2, ..., l)$. At the same time the function should be as flat as possible (Vapnik, 1995). The linear function F is given by:

$$F(x) = \langle w, x\rangle + b,\ where\ w \in \chi, b \in R, \tag{6}$$

which $\langle ., .\rangle$is the scalar product on χ.

Knowing that one searches for a w small, then it is desired and minimize the Euclidean norm $||w||^2$. Thus, the convex optimization problem is given by equation 7 (Smola and Schölkopf, 2004).

$$\min\ \frac{1}{2}||w||^2, \quad \text{liable to:} \begin{cases} y_i - \langle w, x_i\rangle - b \leq \epsilon \\ \langle w, x_i\rangle + b - y_i \leq \epsilon. \end{cases} \tag{7}$$

The optimization problem given by Eqn (7) assumes that exists a function F which approximates all pairs $(\xi,\ y_i)$ with accuracy of ϵ, in other words, the convex optimization problem is feasible (Smola and Schölkopf, 2004). However, there may be no solution to this optimization problem, so two slack variables ξ_i, ξ_i^* are added to cover infeasible constraints. With this, (Vapnik, 1995) demonstrates a new model of equations given by:

$$\min\ \frac{1}{2}||w||^2 + C\sum_{i=1}^{l}(\xi_i + \xi_i^*), \tag{8}$$

$$\text{liable to:} \begin{cases} y_i - \langle w, x_i\rangle - b \leq \epsilon + \xi_i \\ \langle w, x_i\rangle + b - y_i \leq \epsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, \end{cases} \quad \text{where } C > 0.$$

The constant C is determined by the balance between the flatness of F and the amount of deviations larger than ϵ are tolerated. The equation 8 uses the ϵ-insensitive loss function defined by the equation 9.

$$|\xi|_\epsilon := \begin{cases} 0 & \text{if } |\xi| \leq \epsilon, \\ |\xi| - \epsilon & \text{else.} \end{cases} \tag{9}$$

The figure 2 demonstrates the graph as a function of loss . It is notable that samples within the region F(x) $\pm\ \epsilon$ have value equal to zero and outside this region the function has a linear behavior (Vapnik, 1995).

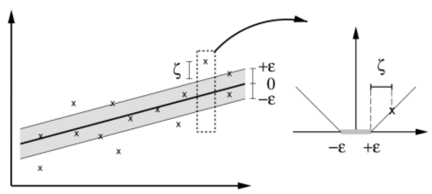

Figure 2. Loss function graph, $|\xi|_\epsilon$.

The regularization parameters, C and ϵ, were declared with a certain operating range to build an optimal correlation for this model. For a more in-depth understanding of the theoretical foundation of SVR can be found in the articles (Junior and Moreno, 2019), (Vapnik, 1995) and (Smola and Schölkopf, 2004).

Considering a more specific description of the application, this tool aims to perform an estimation from a set of noisy observations presented to the system input. The SVR model can be seen as a black-box, obtaining only the desired inputs coming from a well with data exported from the Marlim software in order to estimate a parameter in the output of the SVR. The block diagram that will be studied based on the SVR model is being demonstrated in figure 3.

The purpose of using the machine learning model based on the trained data fetched from the history (with fixed GOR or BSW, choke pressure, PI or injection flow rate), is to somehow obtain an estimation of the GOR or BSW through the SVR tool. In Figure 3 it is shown which variables are possible to use as breakpoints in Marlim. Based on this, a model of inputs and outputs is built for the SVR that influence the desired estimation parameter.

When it comes to parameter fitting, the SVR algorithm relies on the Radial Basis Function (RBF) kernel, known for

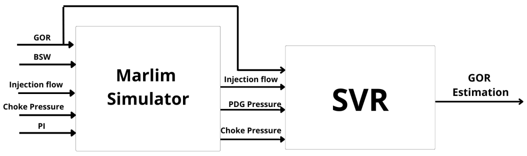

Figure 3. block diagram based on GOR estimation.

its superior estimation performance. The cross-validation techniques for the SVR model involve selecting inputs that exert influence on the parameters of the physical process described by the equations in the Skogestad model, with the inclusion of the water fraction. These equations are represented as 1, 2, and 3. As a result, variables that are not present in these model equations do not affect the estimation of the desired parameter.

Furthermore, when building the SVR model, it was constrained that the algorithm could not estimate the GOR and the BSW simultaneously, as it would cause infinite solutions for the system.

3.2 Convolutional Neural Network (CNN)

We chose to implement a 1D CNN for our problem domain, considering its advantages in time series predictive tasks.

The ability of 1D CNNs to learn complex relationships and mappings between input variables makes them an ideal choice for predicting GOR and BSW in the oil and gas industry, given the intricate nature of the data and the numerous influencing factors.

A 1D convolutional layer uses multiple learnable filters or kernels to convolve with the input data and generate feature maps. These feature maps represent the presence of learned features at different spatial locations in the input. Mathematically, the 1D convolution operation is defined as:

$$y_i = \sum_m I_{(i-m)} K_m \tag{10}$$

where I is the input data, K is the kernel or filter, and y_i is the output feature map. In comparison, the 2D convolution operation is defined as:

$$y_{ij} = \sum_m \sum_n I_{(i-m,j-n)} K_{mn} \tag{11}$$

A sample CNN architecture includes Conv1D, MaxPooling1D, Flatten, Dense layers, and a Dense output layer, and non-linear activation functions, such as Rectified Linear Unit (ReLU), introduce non-linearity into the network, allowing the CNN to learn complex relationships between input variables. Here we chose to apply the widely-used activation function Rectified Linear Unit (ReLU). The ReLU activation function is defined as:

$$f(x) = \max(0, x) \tag{12}$$

where x is the input to the activation function, and $f(x)$ is the output.

4. EXPERIMENTS AND RESULTS

4.1 Data collection and Methodology

This section provides an overview of the data sources and methodology used in the study. The data used in this study comprises two separate types of sources. The first type is simulated data generated by the Marlim simulator, while the second type is real-world data collected from around 10 oil rigs.

For the initial training and testing phase, only the Marlim simulated data was used. Both the support vector regression (SVR) and neural network (NN) models were trained on the same dataset with an 80/20 training-test split. This means that 80% of the data was used for training the model, while the remaining 20% was used to evaluate the model's performance.

The data-set incorporated in this study encompassed 9,600 distinct data points, with variable values spanning from their minimum to maximum realistically achievable values. We chose this wide range of values to establish a diverse and comprehensive data-set suitable for training both the SVR and NN models.

We first created, separated, and indexed the simulated data-set before integrating its components into a vector.

$$\mathbf{x}_i^\top = [Whp_i \ GOR_i \ BSW_i \ PI_i \ qgl_i \ qo_i] \tag{13}$$

Where Whp is the Well's head pressure, qgl the flow of gas from the annulus to the tubing and qo being the total oil flow rate. The learning algorithms employed for this work were implemented using Python and its numerical libraries.

4.2 Experiments with SVR

To replicate a realistic well model, certain parameters need to be estimated using inputs generated by the Marlim field data. Conducting a sensitivity analysis on the Marlim results involves considering inputs such as injection flow rate, choke pressure, variations in GOR, productivity index, and BSW content. Based on this analysis, we developed an SVR model where the GOR parameter serves as the output. The model takes inputs such as injection flow rate, choke pressure, and PDG measurements. The PDG data is an output generated by the sensitivity analysis conducted on Marlim's data.

The first experiment using the SVR estimator was set up in Marlim applying variations of GOR, choke pressure and gas injection flow rate. For the SVR machine learning model, the choke pressure, injection flow and PDG pressure were included as inputs, and the GOR was classified as system output for all the experiments. Figure 4 illustrates that the predictions of the SVR model exhibit discrepancies when compared to the actual values of the estimated parameter. Additionally, the Mean Squared Error(MSE) for this case was quite high, reaching a value of 135,55.

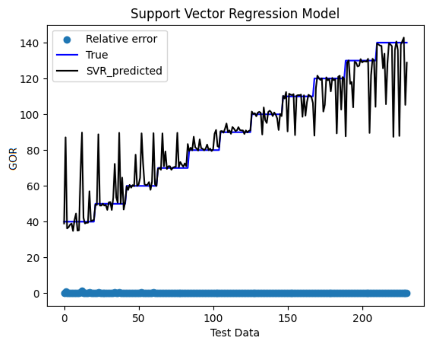

Figure 4. First experiment estimating the GOR.

This can be attributed to the occurrence of three distinct variations within this case(choke pressure, injection flow and PDG pressure).

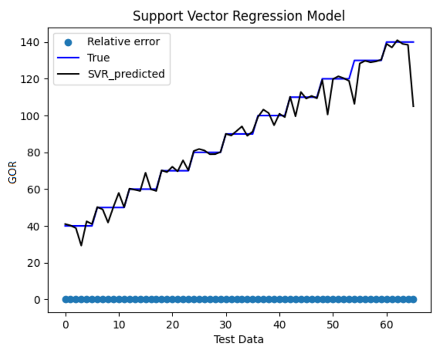

Figure 5. Second experiment estimating the GOR.

Therefore, in the second experiment, only variations in GOR and injection flow rate were introduced for the Marlim case study, while the remaining parameters were held constant(choke pressure, PI and BSW). The SVR model inputs included only the injection flow rate and PDG pressure. As depicted in Figure 5, the predictive model exhibited improved correlation compared to the first experiment, yielding an MSE of 41,52. However, it's important to note that even in this case, there are instances where the predicted values diverge from the actual estimates in the test data, indicating some level of prediction discrepancy.

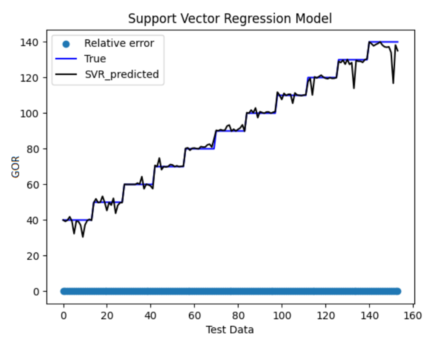

Figure 6. Third experiment estimating the GOR.

In the third experiment, the only parameters that were modified in the Marlim case study were variations in GOR and the choke pressure, keeping constant the parameters BSW, PI, and the injection flow rate. The SVR model used PDG and choke pressure as inputs. As depicted in Figure 6, a noticeable improvement in behavior can be observed compared to the previous experiment. By incorporating additional variations in the Marlim case, the model achieved a significantly reduced MSE of 9,59.

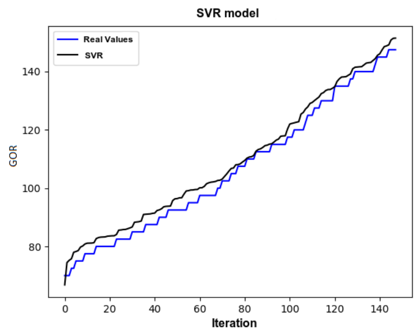

Figure 7. Fourth experiment estimating the GOR.

Based on the conducted experiments, certain refinements were made to the hyperparameters C and ϵ of the SVR model, along with adjustments to the variability of break-points. These changes influenced the variation of GOR, gas injection flow, and choke pressure in the Marlim model, while maintaining BSW and PI constants. Within the SVR model, only the injection flow and PDG pressure remained as input variables. Figure 7 illustrates that the estimated model exhibits a remarkably high correlation, effectively approximating the actual GOR value with minimal deviations. The average relative error for the fourth experiment was 3%, indicating a highly favorable performance of the SVR Tool in estimating the GOR parameter.

4.3 Experiments with CNN

This section contains the details of the configuration processes with the Marlim software and the CNN. To obtain similar results of a real well model, we estimate some parameters based on inputs generated by Marlim. In this paper, BSW and GOR will be set up as the desired parameters for estimation. Thus, after obtaining the analysis of the results generated by Marlim, the CNN model was implemented with the GOR parameter as the output of the system. The inputs for the model are: well head pressure,injection flow rate, PDG, oil flow rate, PI and BSW.

The first experiments using the CNN estimator were set up in Marlim applying variations of GOR, choke pressure, gas injection flow rate, and productivity index, while keeping BSW values constant. For the CNN machine learning model, the well head pressure, injection flow, PDG pressure, oil flow rate, PI, and BSW were included as inputs, and the GOR parameter was classified as system output. In the initial tests, the potential of the CNN model was quickly recognized as it achieved high accuracy without extensive optimization. The model demonstrated a precision beyond 90%, which was a promising start. As the experiments progressed and the model was further fine-tuned, the R-squared (R^2) value reached an 0.9675 value, showcasing the model's excellent performance, as depicted in Figure 8.

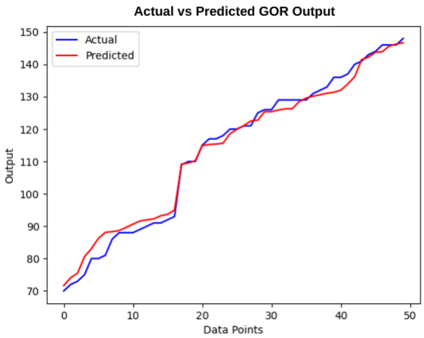

Figure 8. R-squared value of 0.9675 for the CNN model

For a new batch of experiments, we decided to explore the potential of the CNN model in predicting GOR with a varying BSW, based on the promising results obtained during the previous tests where BSW was kept constant. Predicting GOR accurately while considering varying BSW values or vice versa is a significant challenge and would demonstrate the robustness and adaptability of the model in real-world scenarios. We optimized the CNN model by exploring different hyperparameters and architectural changes, employing techniques like adjusting the learning rate, batch size, and layer configurations to find the optimal setup. After several iterations, the CNN's predictive capabilities improved significantly, maintaining high precision and outperforming initial results, underscoring the value of optimization.

Figure 9 showcases the initial accuracy of the CNN model with varying BSW values. This demonstrates the potential of the model in the early stages of the experiments.

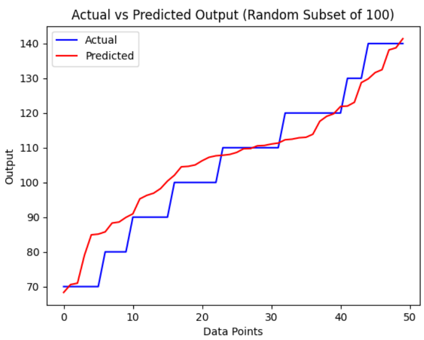

Figure 9. Initial accuracy of the CNN model with varying BSW

As the experiments progressed and the model was further optimized, we achieved a state-of-the-art CNN model that is able to reach an impressive R-squared (R^2) score of 0.994 and a Mean Squared Error (MSE) of 7.91 while using Marlim for training and testing with varying BSW values, as shown in Figure 10.

The same neural network that is capable of predicting the GOR is also capable of predicting BSW with even greater precision, since that value is easier to determine.

Building upon the success of the optimized CNN model, we decided to further challenge its robustness and generalization capabilities by testing it with real-world measurements, while still training the model with Marlim-generated data. This experiment aimed to investigate the model's ability to adapt to real-world data, which may contain uncertainties and noise not present in the synthetic data generated by Marlim. In this part of the experiments, the model was put to the test against field measurements obtained from actual well performance data. It is important to note that the transition from synthetic data to real-world data may introduce discrepancies and affect the model's performance, as the complexity of field data can be higher.

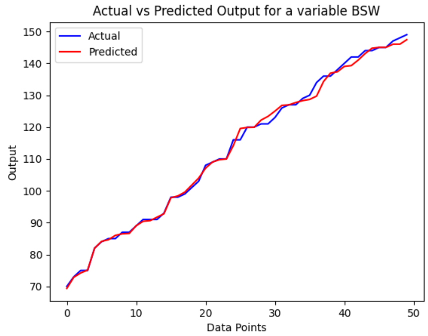

Figure 10. Predicted and real GOR values: R-squared score of 0.994 and MSE of 7.91

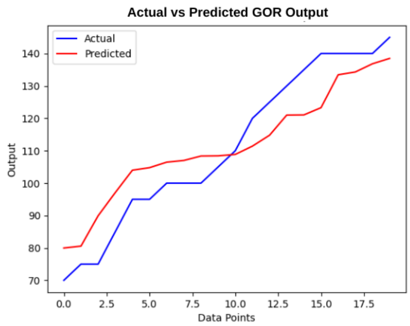

Figure 11. Performance metrics of the CNN model with real-world measurements without access to PI: R-squared score of 0.62

The results of the experiment with real world test data showed a decrease in the model's precision, dropping from an R-squared score of 0.98 to 0.62 when tested with real-world measurements. This reduction in performance can be attributed to not only the inherent complexities and uncertainties present in field data that are not captured in the Marlim-generated synthetic data, but also the fact that the PI was not available for training and testing, thus, reducing the availability of information to our neural network. Figure 11 illustrates the performance metrics of the CNN model when tested with real-world measurements. Although the precision has decreased in comparison to the results obtained with synthetic data, the model still demonstrates a reasonable level of accuracy, considering the complexity of real-world data. These results indicate that the CNN model could potentially be further improved and adapted for real-world applications, especially with access to more data and with additional fine-tuning and optimization to account for the unique characteristics of field data.

The experiments performed help to illustrate the effectiveness of the various optimization techniques employed and the overall success of the CNN model in predicting BSW and GOR, even when considering varying BSW values. The results highlight the potential of the CNN model as a powerful tool for well performance estimation in the oil and gas industry.

4.4 Model Comparison

While both the models showed promise, the CNN consistently outperformed the SVR in terms of precision and capability. For instance, the CNN model achieved an impressive R^2 score of 0.9675 when predicting the GOR with a constant BSW as can be seen in Figure 10, while the SVR model struggled to reach an R^2 score of 0.94, wich can be confirmed by analizing Figure 7. Moreover, the CNN model was able to accurately predict the GOR values even when the BSW was allowed to vary, a task that the SVR model could not accomplish.

Combining all these factors, we can deduce that the SVR is inferior to a CNN when analyzing a time series, especially in our case, where we are analyzing a very complex one. The reason for the CNN's superior performance may be attributed to its various inherent advantages, such as automatic feature learning, localized pattern detection, hierarchical feature representation, robustness to noise, scalability, and end-to-end training. These properties enable the CNN to capture complex patterns and dependencies within the time series data, leading to more accurate predictions.

Our experiments demonstrate that the CNN model is better suited for this specific problem domain compared to the SVR model.

5. CONCLUSION

By employing models from the machine learning literature such as the SVR and the CNN, we have succesfully identified the MARLIM model of an oil well in steady state. We have also demonstrated from experiments that the CNN performs better with the available data, and the fact that, when tested against real data, the CNN strategy still has a positive correlation, even though data is gathered from different sources. This opens up further research in relation to mixing MARLIM simulation data with their real counterpart, as the real counterpart may be scarce.

In light of the promising results achieved by the CNN model in our experiments, we plan to continue our research by focusing on one main objective, developing a context-based neural network. To generalize our approach to wells without Marlim models, we will develop a context-based neural network that can accurately predict well behavior based on the available data and contextual information. This new model will leverage the insights gained from our experiments with the CNN and Marlim data. By doing so, we aim to create a more versatile and adaptable predictive model which we hope will be able to accurately predict the BSW and GOR of real world oil wells without needing an already existant Marlim model to train.

REFERENCES

AL-Qutami, T.A., Ibrahim, R.B., Ismail, I., and Ishak, M.A. (2018). Virtual multiphase flow metering using diverse neural network ensemble and adaptive simulated annealing. *Expert Syst. Appl.*, 93, 72–85.

Bikmukhametov, T. and Jäschke, J. (2020). First principles and machine learning virtual flow metering: A literature review. *Journal of Petroleum Science and Engineering*, 184, 106487.

Bishop, C.M. (2006). *Pattern Recognition and Machine Learning (Information Science and Statistics)*. Springer-Verlag, Berlin, Heidelberg.

Hashemi Fath, A., Madanifar, F., and Abbasi, M. (2020). Implementation of multilayer perceptron (mlp) and radial basis function (rbf) neural networks to predict solution gas-oil ratio of crude oil systems. *Petroleum*, 6(1), 80–91.

Jahanshahi, E., Skogestad, S., and Hansen, H. (2012). Control structure design for stabilizing unstable gas-lift oil wells. *IFAC Proceedings Volumes*, 45(15), 93–100.

Jahn, F., Cook, M., and Graham, M. (2008). *Hydrocarbon Exploration and Production*. Developments in Petroleum Science 55. Elsevier, 2nd ed edition.

Jordan, M., Kearns, M., and Solla, S. (1997). Proceedings of the 10th international conference on neural information processing systems.

Junior, D.H. and Moreno, U.F. (2019). Estimação de pressão de fundo de poço utilizando svr e ukf. In *Congresso Brasileiro de Automática-CBA*, volume 1.

Karniadakis, G.E., Kevrekidis, I.G., Lu, L., Perdikaris, P., Wang, S., and Yang, L. (2021). Physics-informed machine learning. *Nature Reviews Physics*, 3(6), 422–440.

Ko, C.N. and Lee, C.M. (2013). Short-term load forecasting using svr (support vector regression)-based radial basis function neural network with dual extended kalman filter. *Energy*, 49, 413–422.

Sandnes, A.T., Grimstad, B., and Kolbjørnsen, O. (2021). Multi-task learning for virtual flow metering. *Knowledge-Based Systems*, 232, 107458.

Seman, L.O., Miyatake, L.K., Camponogara, E., Giuliani, C.M., and Vieira, B.F. (2020). Derivative-free parameter tuning for a well multiphase flow simulator. *Journal of Petroleum Science and Engineering*, 192, 107288.

Smola, A.J. and Schölkopf, B. (2004). A tutorial on support vector regression. *Statistics and computing*, 14(3), 199–222.

Thanh, H.V., Sugai, Y., and Sasaki, K. (2020). Application of artificial neural network for predicting the performance of CO2 enhanced oil recovery and storage in residual oil zones. *Scientific Reports*, 10(1).

Vapnik, V. (1995). The nature of statistical learning theory. 840 springer-verlag new york. *Inc., New York, NY, USA*, 841, 842.