Digital Twin of a Horizontal Three-phase Separator in an Offshore Oil Extraction and Processing Platform using NARX Neural Networks

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Abstract: Offshore oil extraction presents several challenging scenarios from exploration to operation. Limitations in physical space impose restrictions on the construction of vessels that have sufficient capacitance to absorb the accentuated load variations to which this process is subject. This factor, allied to the turbulent nature of the flow into the risers, which causes occasional slugs, brings high complexity to treatment and separation vessels level control, upon which the quality of the final products depends. The present work takes advantage of recent advances in process identification techniques to develop a NARX-type neural network to carry out a Digital Twin implementation of a three-phase separator of an offshore unit, located in the Campos basin, Brazil. The Digital Twin allows simulations of different control techniques to be tested in a realistic simulation environment, as it uses heuristics and machine learning techniques capable of inferring even nonlinear relationships between variables, mirroring the physical twin behavior. The main goal is to enable these simulations to be run and achieve enhanced process control. The results obtained in the present work show that it is possible to obtain a Digital Twin using NARX-type neural networks with Mean Absolute Percentage Error marks below 1% in test situations to predict main chamber and oil chamber levels, which can be used to simulate and benchmark advanced level control strategies.

Keywords: Digital Twin; NARX; Neural Networks; Petroleum; Separator; Treatment; Modelling; Offshore.

1. INTRODUCTION

Currently, the Oil and Gas industry is responsible for approximately 13% of Brazil's Gross Domestic Product figure (Agência Nacional do Petróleo, Gás Natural e Biocombustíveis, 2020). In 2021, 97% of the country's oil and gas production was extracted offshore (Agência Nacional do Petróleo, Gás Natural e Biocombustíveis, 2022). This is a very challenging production environment for several reasons, among which is possible to highlight the low availability of physical space, which generates difficulties for the controllers, given the separation vessels' low capacitance. Therefore, production facilities are not able to absorb the extreme load variations caused by well production flow instability (Campos et al., 2015). There are many reasons that can cause well production flow instability like the transients caused by production wells opening and closing, the turbulent characteristics of multiphase flow, and slugs, among others. Slugging flow is one the most common perturbation causes and one with higher severity potential, overloading separators, causing gas flaring, harming separation efficiency, and potentially even damaging equipment like heat exchangers, valves, and pipes, that may result in elevated maintenance and operational costs (Nnabuife, Tandoh, and Whidborne, 2022). Fig. 1 (Hansen et al., 2022) shows an oil extraction and treatment schematic vision, from the reservoir to the treatment plant.

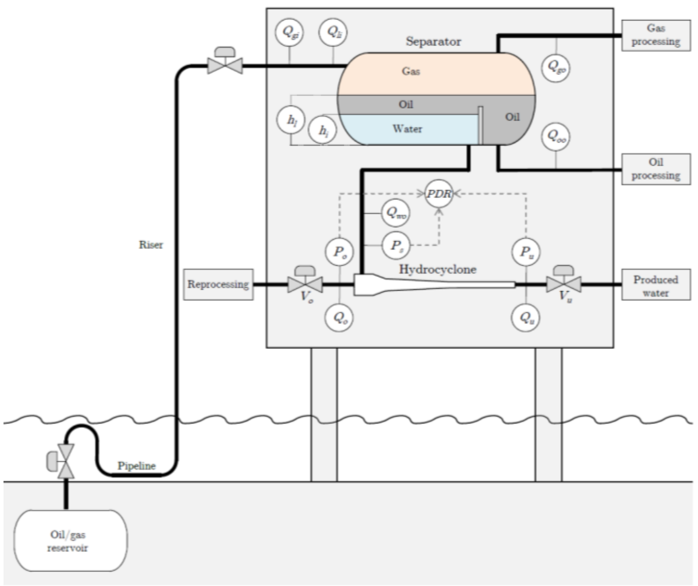

Fig. 1 Offshore Oil Extraction plant.

In figure 1 it is possible to observe that the three-phase separator is the first equipment in the process and is responsible for receiving the crude oil stream, which is a mixture of gas, produced water, and oil, and dividing it into three streams that are processed individually to achieve the production standard parameters. Therefore, given the importance of the three-phase separator in the process and how prone the wells’ production flow is to be unstable, it becomes evident the need for control strategies that have enough robustness to maintain process stability even in the most severe conditions, while also having the quickness to respond to abrupt load variations. PID control is often used in offshore oil extraction platforms, even though it does not perform well enough when the process dynamics vary too much. Frequently used in the refining and petrochemical industry, advanced control techniques are still scarcely applied in the offshore petroleum industry. (Campos et al., 2015) Historically, there are a few hurdles that have been imposed to the wide use of advanced control in oil platforms (Campos et al., 2009). However, in order to avoid many of these hurdles, it is possible to model and simulate the processing plant's behavior, allowing further testing and comparative evaluation that is close to the real plant behavior. According to Tuegel et al, 2011 “a Digital Twin is an integrated Multiphysics, multiscale, probabilistic simulation of an as-built system that uses the best available physical models, sensor updates, historical data, etc. to mirror the life of its corresponding physical twin” and present benefits in comparison with commercial simulation software since it is a rigorous integrated representation of the process chosen. The Digital Twin development is a huge advance in industry, given the possibility of running realistic simulations in the virtual world, allowing, for example, the simulation and comparison of different process control strategies. The obtained model while developing a Digital Twin can be very precise and specific, allowing for more audacious tuning, by following the idea that a digital twin has roughly the same response as the physical one (Kritzinger et al., 2018).

Several techniques are being applied to Digital Twins development lately, as it is rapidly gaining steam and popularity in the industry these days. Among these techniques, the use of neural networks can be highlighted, owing to their capability of emulating even the most complex functions behavior. Given the real processes nature, the most commonly used neural networks are the ones that consider past states of variables of interest, dividing the field of study into two main streams: Recurrent Neural Networks (RNNs) and Autoregressive Neural Networks. The main difference between them is the way they learn long-term dependencies. In RNNs there are signal feedback mechanisms, propagating them through the network for a set amount of time, influencing the upcoming outputs for a while. As a downside, these networks are prone to the vanishing gradient problem, that arises in deeper networks and results in learning difficulties and overall inaccuracy of the networks (DiPietro et al., 2018). Autoregressive networks approach this feedback situation differently, using the past variable states as new inputs, which can be viewed as an orthogonal way of dealing with past states, concerning common RNNs (Liu et al., 2020). The information flows differently in NARX neural networks compared to RNNs, given that NARX models are fed the n-latest outputs as well as the inputs at every new iteration, while RNNs resonate the past states inside their architecture by using sequencial processing. In the present work, NARX Neural Networks are used in order to develop the Digital Twin of a three-phase separator located in an offshore oil extraction platform located in the Campos basin. This Digital Twin can predict the levels' behavior by looking at the actual and past states of inlet pressure, oil, gas, and water outlets, and the levels. In this paper, the separator pressure is considered constant, given how quick the pressure control is in comparison to every other variable behavior. The main goal of this work is to allow for realistic level control simulations and enable the implementation of advanced control techniques while establishing a working methodology and benchmark values.

2. PETROLEUM TREATMENT

The fluids produced by oil and gas wells are made up of mixtures of natural gas, crude oil, and salt water. Such mixtures are difficult to handle and measure, and their transportation poses environmental risks and is economically unviable. For this reason, exporting oil and gas from extraction sites (offshore platforms or onshore wells) to storage or refining sites requires a treatment step known as Primary Oil Processing (Abdel-Aal, Aggour, and Fahim, 2003).

The first separation equipment is the three-phase separator, from which currents of water, oil, and gas are extracted and sent to specific treatments to adjust these products to standardized parameters of humidity, oil, and grease content, among others. From there, the oil goes to electrostatic treaters, which aim to perform the agglutination of water droplets present in the oil by electrostatic means, to speed up the separation process. The water coming from the three-phase separators and electrostatic treaters, in turn, goes to the hydro cyclones, where the first stage of oil removal is performed by whirling, increasing separation velocity caused by the density difference between water and oil. Next step, the water goes to the flotation vessels, for the final removal of the oily residue by dissolved gas flotation and injection of coagulant/flotation products, such as polyelectrolyte, and is then discarded into the sea or reinjected into the injection wells. The gas prevenient from the separation process goes to the compression unit where its pressure is raised to the working pressures of the fuel gas, gas lift, and exportation plants. This gas goes through several stages of dehydration and particulate removal to meet the standards and avoid hydrates formation (Triggia et al., 2001). A typical control performed in the three-phase separator has 3 controllers:

- Pressure controller: responsible for relieving the separation pressure, while still maintaining sufficient pressure to ensure the flow of the separation products. Opening the pressure control valve sends the gas to the treatment and compression stages. In this paper, the Digital Twin is developed considering the pressure as a constant, given how quickly the pressure controller response is in comparison to every other variable behavior;

- Main chamber level controller: it is the separator main controller, responsible for establishing the cut-off point between the fluid in the main chamber and the fluid that pours into the oil chamber, through the weir. Level sensors measuring the oil-water interface are not accurate enough to guarantee a permanent setpoint adjustment. The choice of setpoint is an interactive process of observing the quality of

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the products (oil and water) and thus evaluating the quality of separation for the choice of interface level. This also varies with the process temperature, which can help or hinder the breaking of emulsions and can cause the need of a higher or lower set of the interface. The stability of this controller is paramount to ensure an adequate separation process and to avoid the accumulation of water pockets in the oil chamber, or even the flow of oily products to the water outlets.

- Oil chamber level controller: Responsible for maintaining a column of liquid between the three-phase separator and the rest of the oil treatment process, avoiding the passage of gas to the rest of the treaters. The controller behavior directly influences the flow oscillation to the equipment downstream of the separator, hence being the controller responsible for the electrostatic treater load control. Fig. 2 (Campos et al., 2015) shows a very didactic graphical representation of how the fluids flow in the three-phase separator.

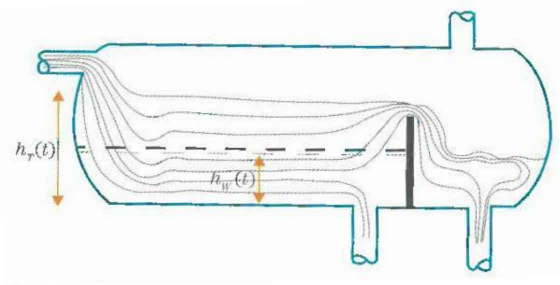

Fig. 2 Flowlines detailing the separation process.

In figure 2 it is possible to see how the difference in density between oil and water is responsible for the separation process, and the division inside the separator into two chambers: the main chamber and the oil chamber. The oil, having less mass density than water, flows in the upper section and can overflow the weir, a wall that is responsible for dividing the chambers. Given the variations in crude oil composition, it is crucial that the interface level is controlled carefully since the separation quality will be a direct result of the main chamber level control. Lower levels in the main chamber may result in oil that has less water concentration, but on the other hand, may result in water being contaminated with more oil and emulsion. Higher levels in the main chamber prevent oil from being sent to the water outlet but also can result in oil receiving bigger quantities of water. These situations described here demonstrate the importance of having good control of the main chamber level, as variations also can be detrimental to product quality. As for the oil chamber level, its level control is important for having a seal that does not allow gas to migrate to the oil stream, so a minimum level is needed. Also important is to maintain the valve variations to a minimum, since its modulation is what dictates the electrostatic treaters' load input. The objective is to absorb level fluctuations without losing the liquid seal that protects the oil stream from gas contamination.

3. NARX NEURAL NETWORKS

A NARX network is a Non-linear AutoRegressive model that has eXogenous inputs, which means that this model relates current and past data from a time series with current and past data from the exogenous series, that is, the network's output signals are fed back to the input to participate in a next stage, giving this network the ability of temporal comprehension.

The main difference between NARX networks and other well-known RNNs such as LSTM (Long Short-Term Memory) and vanilla RNNs, is the output data feedback architecture. In most of the RNNs proposed in the literature, an important limitation lies in the vanishing gradient issue, which is the loss of information as the number of layers in the network increases, being a detriment to performing learning for problems that require more long-term memories. One of the alternatives to circumvent this problem is the advent of LSTM networks, using activation functions and layer by-pass gates that allow the propagation of past signals over a longer time interval, giving the networks greater memory retention capacity. Differently, NARX networks adopt a perpendicular approach concerning common RNNs and LSTM networks by using past state signals as inputs simultaneously with current signals, in a parallel manner, differing from the sequential feedback used by common RNNs, allowing greater control over the number of past responses and the amount of time that must be considered when predicting a future output (Henaff, Szlam, and LeCun, 2017). Fig. 3 (DiPietro et al., 2018) illustrates the information flow differences between LSTM networks, simple RNNs, ordinary NARX networks, and NARX networks with exponential delay.

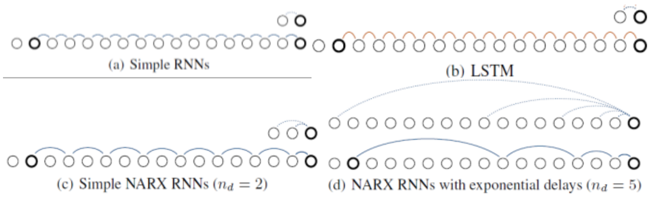

Fig. 3 Common RNNs x LSTM x Simple NARX x Exponential NARX.

In figure 3 the information flow is represented by slurs, and it can be seen how common RNNs are serialized and receive always the last output state, influencing the next prediction. NARXNNs, on the other hand, can be fed with many past states that can even be non-linear, as can be seen in example d), which uses exponential delays to feed the neural network.

NARX networks can perform black-box modeling, mapping their neurons in such a way as to infer non-linear and even initially unknown relationships, simplifying the realization of modeling complex systems without necessarily simplifying the model itself (Liu et al., 2020). This type of approach also allows the level of expertise required to implement a model to be much more basic, requiring only the ability to critically evaluate the results and their suitability as a solution to the problem at hand (Henaff, Szlam, and LeCun, 2017). A typical NARX neural network configuration is shown in Fig. 4. (Liu et al., 2020)

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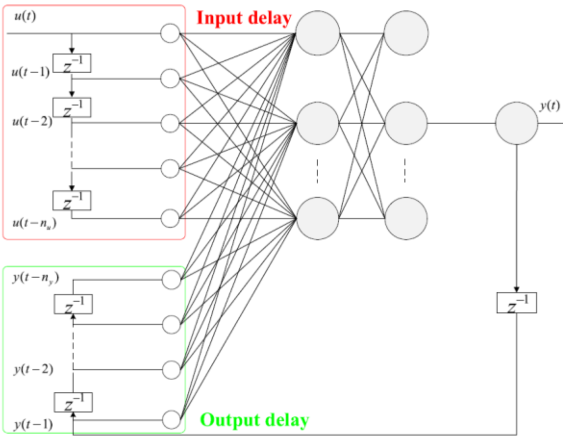

Fig. 4 NARXNN architecture in detail

As shown in figure 4, there is a pre-defined number of delays being fed back to the network, represented by the *n* letter. In order to evaluate and make a decision about the number of delays (or lags) that are going to be used, the autocorrelation of these variables is calculated. The decision is up to the network designer, but the premise here is that the best values are the ones that have high autocorrelation and can represent well how these variables behave through time. It is also important to notice that choosing a high number of lags is going to make the network bigger, and more computationally expensive to train.

4. METHODOLOGY

4.1 Data Extraction, Transformation, and Loading

The process data was collected from the data system used at Petrobras: OSISoft Plant Information (PI). The system is widely used in other industries to support operation and process control, with the possibility of plotting historical process data trends and viewing values in real time. To collect this data for the development environment implemented in Python programming language, using Jupyter Notebooks, the open-source library PIconnect was used. Once the data was imported, the Pandas library was used to create data frames, which facilitates the manipulation and treatment of the data to make it ready to use at later stages. With Pandas it was also performed treatment for missing data, performing the data imputation using the last valid read data, following good practices for time-series.

4.2 Autocorrelation evaluation of inputs and outputs

To perform the autocorrelation evaluation step of the variables, it was used the Statsmodels library, which already has appropriate functions to perform the calculation and plot of autocorrelation functions. With the autocorrelation information of each variable available and easy to visualize, it is possible to determine the number of lags to be used for each input or output variable, as well as the number of internal layers and neurons in the internal layers, following this criteria established by the authors: choose a number of lags that is big enough to represent well the internal state and inertia of the variables, while also being small enough so that the model does not gets too big and complex that would be computationally expensive to train.

4.3 Data preprocessing

After this decision-making process, it is possible to start the implementation of the data preprocessing and neural network creation steps. For these two steps, the Scikit Learn and Pytorch libraries were used. The Scikit Learn library has several very useful tools for preparing data for network training, and in this work, a normalization function called RobustScaler was used. This normalization is very suitable because it can transform data into a distribution extremely robust to outliers by the calculations performed using the median, instead of the mean, and the standard deviation, greatly facilitating the training of the neural network and accelerating its convergence.

4.4 Structure of the developed algorithm

The neural network architecture was then implemented using Pytorch, using linear activation functions. Once the network was created and the data prepared, the model was trained. Since this is a time-series dataset, the training and validation datasets were obtained from the same time window, being the first 90% of the data used for training and the 10% final used for validation. The method used to evaluate the results was interactive, adjusting the number of variable lags, as well as the size of the net (number of internal layers, number of neurons in the internal layers, optimizers, evaluation metrics, etc.). Once the model construction was finished, a test step was performed, predicting the behavior of the variables of interest using new datasets from other periods of the process plant, in order to evaluate the robustness and generalization capacity of the digital twin. For results visualization, the Seaborn library was used, for its simplicity in generating visually comfortable and easily distinguishable graphs, and for its orientation for easy customization of the visualizations.

Fig. 5 shows a schematic diagram of the libraries and functions used by the authors to construct the network design and training, with the detailing of their respective roles in the application.

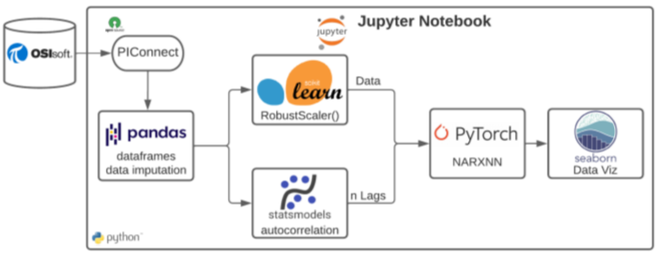

Fig. 5 Libraries and functions used in this work.

4.5 Evaluation metrics

In order to perform the evaluation of the obtained models and interactively adjust the hyperparameters and number of lags of the NARX neural network, 4 evaluation metrics most commonly used in time series prediction were chosen (Matta et al., 2021): (a) Mean Squared Errors (MSE); (b) Root Mean Squared Errors (RMSE); (c) Mean Absolute Error (MAE); (d) Mean Absolute Percentage Errors (MAPE);

- MSE - Is the mean of the squared errors. Due to the exponentiation of the errors to the second power, they are considered independently of negative or positive errors, and their measurement is very sensitive to larger errors. This property is very valuable when you want to find a model that generally approximates real behavior, but it can be an overly harsh metric when outliers occur (Büyükşahin and Ertekin, 2019).

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

- RMSE - Derived from MSE, but uses the square root of the mean square errors. Less susceptible to outliers than MSE, also does not consider the sign of the prediction error.

$$RMSE = \sqrt{\sum_{i=1}^{n}\frac{(\hat{y}_i - y_i)^2}{n}}$$

- MAE - Mean Absolute Error. Using the modulus of the prediction error is an even more robust measure of the presence of outliers than RMSE.

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n}|y_j - \hat{y}_j|$$

- MAPE - Absolute Mean Percent Error, this measure considers the percent ratio between the prediction error and the amplitude of the true variable.

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

5. DISCUSSION AND RESULTS

5.1 Detailing the input and output variables

The variables selected for reading and training the model were based on process experience and observation of their interaction with the desired outputs. They were:

- Separator vessel inlet pressure (Inlet Pressure): important to infer the arrival of more liquid or more gas, from the relationship with output flow rate variations and knowing that liquids are incompressible;

- Gas Flow: indicates the response of the gas outlet valve, in this work considered fast enough to ensure constant pressure in the separator vessel. Very important for the detection of bubbles with the passage of pockets of gas;

- Water Valve Opening: final control element in the main chamber level controller of the of the three-phase separator. The signal from the water exit flow meter could also be used, but it only totals the hourly flow rate, thus losing much of the data of interest to this work;

- Oil Valve Opening: final control element in the oil chamber level controller of the three-phase separator.

- Oil Flow: represents the process output and is used here in an apparently redundant manner with the oil valve opening percentage. But as this system is interconnected to the oil treater and suffers pressure variations depending on the load variation, the flow measurement is of great importance to infer the process flow despite pressure oscillations. It is also an instrument that requires more frequent calibration than the outlet valves, which usually have deposits and scales that compromise its proper flow control.

An example visualization of input variables already normalized is shown in Fig. 6.

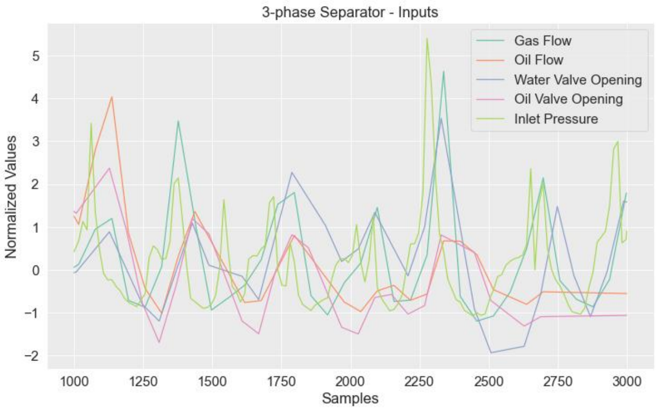

Fig. 6 Input variables visualization.

The output variables are the level values in the main chamber and the oil chamber. A demonstration of the normalized output behavior can be seen in Fig. 7.

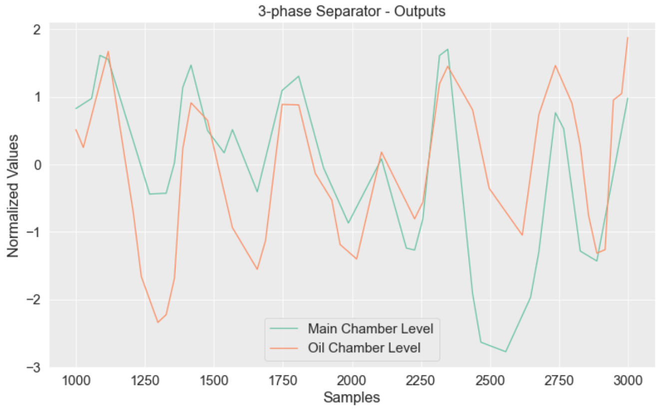

Fig. 7 Output variables visualization.

The collected data used in this work was selected by looking for periods where there were huge loads variation in the separator, and periods where the producing flow was in an unstable regime. The choice for this type of period was based on the premise that this would be the worst case for the process, being challenging to model. It also allows a better visualization since the curves of the process variables are quite pronounced in this situation, allowing a better comparative view. After modeling and testing, this premise was re-evaluated by using stable producing flow pattern data, and it showed even better accuracy than unstable flows, serving as a validation for this premise. The data collected for training and validation refers to an operating period of 18 representative hours.

5.2 Data preprocessing

With the data prepared, a normalization step was performed using the *Scikit Learn* library, taking the precaution to avoid the problem known as data leakage between training and test data (Kaufman, Rosset, and Perlich, 2011). The next step was to evaluate the autocorrelation of each of the input and output variables, in order to select the number of lags to be used. After some stages of training and evaluation, it was possible to realize that the use of older data with high correlation (values greater than 0.9) resulted in models with high prediction performance, but the choice of a bigger number of lags (20-30 lags per variable) resulted in excessively slow models for training and with a large number of parameters to be trained. The data sampling time used was 1 second, but it was possible to observe that even the variable with the sharpest decline in the autocorrelation curve, which was the inlet pressure, presented a correlation above 0.95 for lag values less than or equal to 5. Thus, to avoid changing the sampling time so that there would be no loss of training data, it was decided that the number of lags adopted for the NARXNN would be using values with 5 samples of separation i.e.: $t-5$, $t-10$, $t-15$, etc., thus reducing the number of neurons in the net, while still managing to preserve the amount of data and temporal information of the process.

5.3 Network Training

A commonly used starting point in establishing the number of hidden layers in the network is to select a simpler architecture for initial testing, and if the model obtained shows underfitting behavior, then new hidden layers are added. In the present work, the architecture with one hidden layer was chosen, as it proved to be sufficient for the complexity of the problem in question. Of the various methods proposed, it is not yet possible to say that any of them is suitable for all cases, and a case-by-case evaluation is needed in a careful and interactive manner (Vujičić et al., 2016). The error metric of the training algorithm chosen was MSE, and the optimizer that obtained the best convergence was Adam. After fine-tuning the model iteratively, the neural network obtained had 25 nodes in the input layer, 2 nodes in the output layer and 16 nodes in the hidden layer. The learning rate used was 0.01, training for 100 epochs.

5.4 Validation Results

The validation was performed using the portion with the final 10% of the training dataset, obtaining results for the prediction of the main chamber and oil chamber levels, which can be seen in Fig. 8 and Fig. 9, respectively:

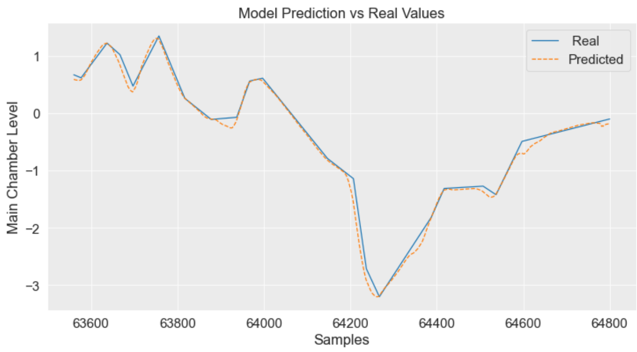

Fig. 8 Model Prediction vs Real Values for the Main Chamber Level in validation.

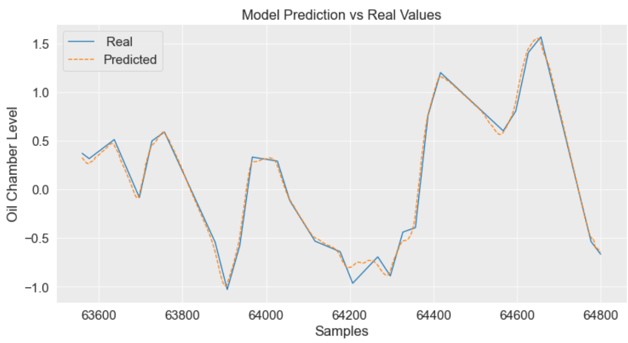

Fig. 9 Model Prediction vs Real Values for the Oil Chamber Level in validation.

These results show that the Digital Twin model was very accurate in predicting the levels even in challenging situations like sharp tendency changes. Some error is still present, but the simulated process is capable of following roughly the same trend and values as the real process.

5.5 Test Results

The tests were performed using data collected during periods of production instability as well as periods of stability. In order to validate the robustness of the Digital Twin, the test #1 was collected from a period approximately 11 months after the training and test dataset, comprising 7h30m of operating data. The results can be seen in Fig. 10 and Fig. 11.

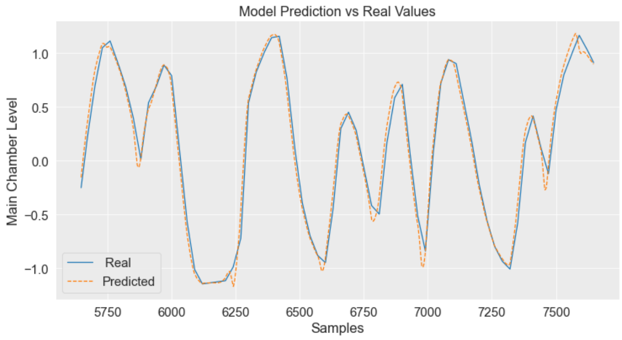

Fig. 10 Model Prediction vs Real Values for the Main Chamber Level in the test set.

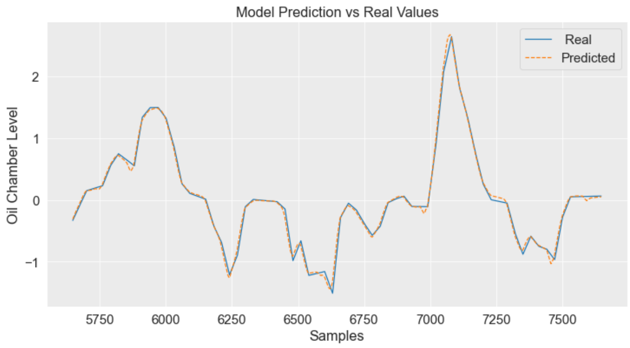

Fig. 11 Model Prediction vs Real Values for the Oil Chamber Level in the test set.

It can be seen that the levels' prediction in the test set is very much accurate and precise, which is a promising sign about the resilience of the model since this test dataset was collected from a period so distant from the validation set. This is a testament to the Digital Twin generalization capability and a good sign that the model is not overfitting training data.

Besides Test #1, another 4 tests were conducted comprising of 8-12 hours of data each, with periods of stability and instability, which demonstrate how well the Digital Twin can generalize. The consolidated results of the evaluation metrics for testing and validation can be seen in table 1. It is possible to see that the metrics are all extremely low, especially important the MAPE metric, which is a percentage error. The MAPE metrics results below 1% show that the Digital Twin is being able to mirror closely the physical twin's behavior in various conditions.

Table 1 – Metrics Results

error	MSE	RMSE	MAE	MAPE (%)
Validation	0.007	0.085	0.063	0.41
Test #1	0.005	0.071	0.052	0.98
Test #2	0.006	0.076	0.052	0.47
Test #3	0.005	0.073	0.043	0.62
Test #4	0.011	0.104	0.075	0.79

6. CONCLUSION

The results demonstrated the ability to develop a Digital Twin of the three-phase separator, using NARX neural networks, with high prediction accuracy even for the proposed tests situation, which represented a challenge to the developed model. The time difference between the training and test #1 datasets (11 months) represents a rather large time window. However, still, the digital twin demonstrated robustness and prediction capability, with a MAPE error metric of around 0.98%. Tests #2, #3, #4, and #5 were conducted using data from stable and unstable periods, between 3 – 9 months later than the data used to train and develop the model, with very accurate results as well. The methodology established in this work can be replicated for the development of Digital Twins for other equipment, and especially for simulation to achieve process control improvements. The implementation of a Digital Twin brings to the simulation environment the necessary realism to achieve huge advances in process efficiency without the need for large investments in equipment or structure, and this work represents a precise and achievable way of implementing that.

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