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Neuro-FuzzyPID flow control logic for subsea oil wells for FPSO processing

Lógica de control de flujo Neuro-FuzzyPID para pozos petrolíferos submarinos para procesamiento FPSO

Lógica Neuro-Fuzzy-PID de controle de vazão de poços de petróleo submarinos para processamento em FPSO

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Abstract

Bearing in mind that emerging underwater oil wells around the world operate with fixed choke valve opening and manual activation, we saw the opportunity to automate this item in order to guarantee better productivity for the process. This article shows how a closed-loop Neuro-Fuzzy-PID control logic was designed to control the production of emerging subsea oil wells in order to maintain continuous power supply to the platform's treatment process and correct disturbances. For this, an artificial neural network was created that resulted in the behavior of the wells depending on the opening of the choke valves and then a Fuzzy-PID controller was implemented that closes the wells' mesh with the platform process. Several simulations were carried out to show the operation of the closed loop, given that Fuzzy-PID control has the great advantage of having a tuning that works even with changes in the process dynamics and for various operating ranges. With this work it was possible to estimate a potential gain of up to 923 thousand reais for the oil platform studied per year.

Keywords: Neural Networks, Fuzzy, Oil wells.

Resumen

Teniendo en cuenta que los pozos petroleros submarinos emergentes alrededor del mundo operan con válvula de estrangulamiento fija de apertura y activación manual, vimos la oportunidad de automatizar este elemento para garantizar una mejor productividad del proceso. Este artículo muestra cómo se diseñó una lógica de control Neuro-Fuzzy-PID de circuito cerrado para controlar la producción de pozos petroleros submarinos emergentes con el fin de mantener un suministro de energía continuo al proceso de tratamiento de la plataforma y corregir las perturbaciones. Para esto se creó una red neuronal artificial que dio como resultado el comportamiento de los pozos dependiendo de la apertura de las válvulas de estrangulamiento y luego se implementó un controlador Fuzzy-PID que cierra la malla de los pozos con el proceso de plataforma. Se realizaron varias simulaciones para mostrar el funcionamiento del circuito cerrado, dado que el control Fuzzy-PID tiene la gran ventaja de tener una sintonía que funciona incluso con cambios en la dinámica del proceso y para varios rangos de operación. Con este trabajo fue posible estimar una ganancia potencial de hasta 923 mil reales por año para la plataforma petrolera estudiada.

Palabras clave: Redes Neuronales, Lógica Difusa, Pozos de Petróleo.

Resumo

Tendo em vista que os poços surgentes submarinos de petróleo em todo o mundo operam com abertura das válvulas choke de forma fixa e com acionamento manual é que se viu a oportunidade de automatizar esse item a fim de garantir uma melhor produtividade para o processo. Esse artigo mostra como foi concebida uma lógica de controle do tipo Neuro-Fuzzy-PID em malha fechada para controle da produção de poços de petróleo surgentes submarinos a fim de manter a alimentação do processo de tratamento da plataforma de forma contínua e a corrigir distúrbios. Para isso foi elaborado uma rede neural artificial que resultou no comportamento dos poços

em função da abertura das válvulas choke e em seguida implantado um controlador Fuzzy-PID que fecha a malha dos poços com o processo da plataforma. Várias simulações foram realizadas para mostrar o funcionamento da malha fechada, sendo visto que o controle Fuzzy-PID tem a grande vantagem de ter uma sintonia que funciona mesmo com a mudança na dinâmica do processo e para vários ranges de operação. Com esse trabalho foi possível estimar um ganho potencial de até 923 mil reais para a plataforma de petróleo estudada por ano.

Palavras-chave: Redes Neurais, Fuzzy, Poços marítimos.

Introduction

Oil production is essential to modern life. Whether for driving vehicles, generating electrical energy or as raw material for manufacturing various components, its level of consumption is even used to measure the development of a nation, where Costa (2014) confirms this view by stating that Due to the fact Today it is difficult to find a product that does not contain oil or its derivatives or that does not have the direct or indirect involvement of oil in its production chain, it can be seen that the world market is almost completely focused on the consumption of oil and its derivatives.

In Brazil, oil production is mostly carried out at sea (CHAVES, 2021). Petrobras is the largest national producer. Thus, to enable production, Petrobras uses platforms that were built to receive and safely separate the various fluids produced by submarine wells and allocate these fluids for export by ships or pipelines or inject them into the reservoir for secondary recovery or disposal, being for this purpose, it is equipped with an oil, water, gas and utilities treatment system.

On oil platforms, wells are normally operated manually by opening or closing the production choke valve of each well and therefore depend on the reaction time of the platform operator to be activated. In many cases, the plant operates below the nominal production level, as activating the valve to increase well production depends on the visualization of the deviation and the operator's action to correct this deviation and this does not always happen at an adequate speed. The slug production system itself, resulting from the production of fluids by several risers, generates an oscillatory behavior that can bring instabilities to the process and difficulties in processing. See figure 1 for the interconnection diagram between wells and platform.

In this state-of-the-art scenario, we have Artificial Intelligence (AI), Machine Learning (ML) and Data Science (DS) among the technologies that can be used to enable oil production safely and efficiently. These techniques apply engineering knowledge to the operation of machines, equipment, tools and/or applications with decision-making and learning capabilities, where several technologies have already been developed for practical application, such as fuzzy logic, or fuzzy logic, and learning of machines using neural networks, techniques that have been successfully applied throughout the world, according to Bello et al. (2016). Torres Campos (2020), states that with the pandemic and the need for computerization and automation of processes to promote less need for personnel to operate plants, the more we apply techniques such as those mentioned, the better the process optimization will be.

Although traditional control is widely used due to its ease of implementation and the large amount of information already prepared about its models, there is no guarantee that these models are the most suitable for modern processes, as the complexity of plants has been increasing with age. time and therefore the complexity of control systems should follow the same rhythm. Nunes (2010) confirms this when saying that "strict control of offshore processing variables guarantees operational continuity, but does not economically optimize processing" and Nunes (2010) reinforces this view as he states that "Emphasis should be given to the global trend greater complexity of processing plants due to the search for oil in regions previously considered economically unviable or unattractive", a description that fits the situation under study.

Still as a justification, we have that the technological challenges for oil exploration in ultra-deep waters permeate conventional exploration and production techniques. According to Campos et al. (2017), environments that present extreme situations of temperature, pressure and the presence of contaminants, such as CO2, require new approaches to enable production with reference efficiencies for the processes.

Thus, this research will aim to show how the implementation of a neuro-fuzzy-PID well flow control system can be used as a new production technology for a real FPSO type platform currently installed in the Brazilian pre-salt, having as focus on obtaining prospects for production gains in order to add value to Petrobras and other companies in the sector, contributing to a more stable platform operation and sustainable industrial development, with a safe working environment and answering the following question search:

"How to control well production using neural networks and fuzzy logic in order to safely increase the production of an FPSO-type platform?"

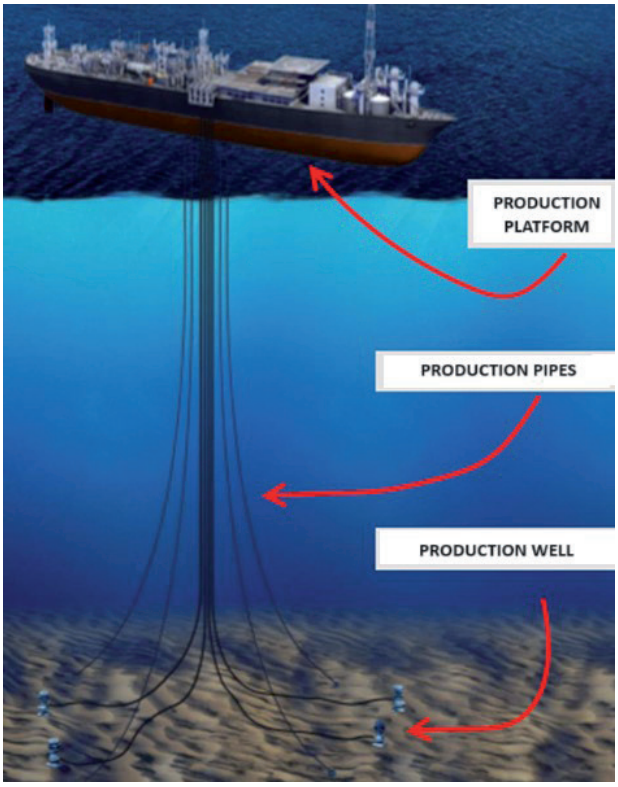

Figure 1: Interconnection scheme between wells and a platform.
Source: Crivellari (2016).

Methodology

For the proposed system to be created, it is first necessary to simulate a process plant with the characteristics present in the platform under analysis in order to include the proposed artificial intelligence system and evaluate its gains. For this, the simulation developed, validated and presented by Chaves (2021) was used as shown in the figure below:

In figure 2 it is possible to observe that the process begins with the wells and ends in the cargo tanks, where the current condition of the platform under analysis is a process formed by five producing wells, a three-phase separator that operates as two-phase due to the non-significant production of water through the wells currently, four treatment vessels (2 degassers and 2 electrostatic), two shell and tube heat exchangers, a compact plate heat exchanger and a platform storage tank (Cargo tanks). In addition to the equipment previously mentioned, the plant contains a compact plate heat exchanger for heating water for the oil desalination stage, however it was not included in the simulation, as this stage is not currently being used for real conditions and Therefore, the dilution step for desalination was not included.

In the simulation carried out in this study we focus on the interface between the wells and the process, in this case the modeling of well production by the choke, which will be represented by the neuro-fuzzy system, and the separator vessel becomes important, as it is the one that will receive production from all wells and still have its output controlled by the system created. Thus, the equations that are used to model the separator according to what is presented in the work of Nunes (2010):

$$\frac{dh_L(t)}{dt} = \frac{L_{in}(t) - L_{out}(t)}{2C\sqrt{[D - h_L(t)]h_L(t)}} \quad (1)$$

$$\frac{dP(t)}{dt} = \frac{P(t)(G_{in}(t) - G_{out}(t) + L_{in}(t) - L_{out}(t))}{V - V_L(t)} \quad (2)$$

$$L_{out} = 2{,}4.10^{-4}.C_v f(x)\sqrt{\frac{\Delta P_v}{\rho_L/\rho_w}} \quad (3)$$

$$G_{out} = 2{,}4.10^{-4}.C_v f(x)\beta\varepsilon P(t)\sqrt{\frac{(P(t) - P_2)}{P(t)ZT\left(\frac{\rho_g}{\rho_{ar}}\right)}} \quad 4)$$

$$V_L(t) = \frac{C_1 {D_1}^2}{4}\left[arccos\left[\frac{D_1 - 2h_L(t)}{D_1}\right] - \left[2\frac{\sqrt{(D_1 - h_L(t)h_L(t))}}{D_1}\right]\left[\frac{D_1 - 2h_L(t)}{D_1}\right]\right] \quad (5)$$

Where:
$V_L\,(t)$: Volume of liquid in the vessel (m^3);
$V\,(t)$: Vessel volume (m^3);
ρ_L: Specific mass of the liquid (kg/m^3);
ρ_G: Specific mass of the gas (kg/m^3);
ρ_{ar}: Specific mass of air (kg/m^3);

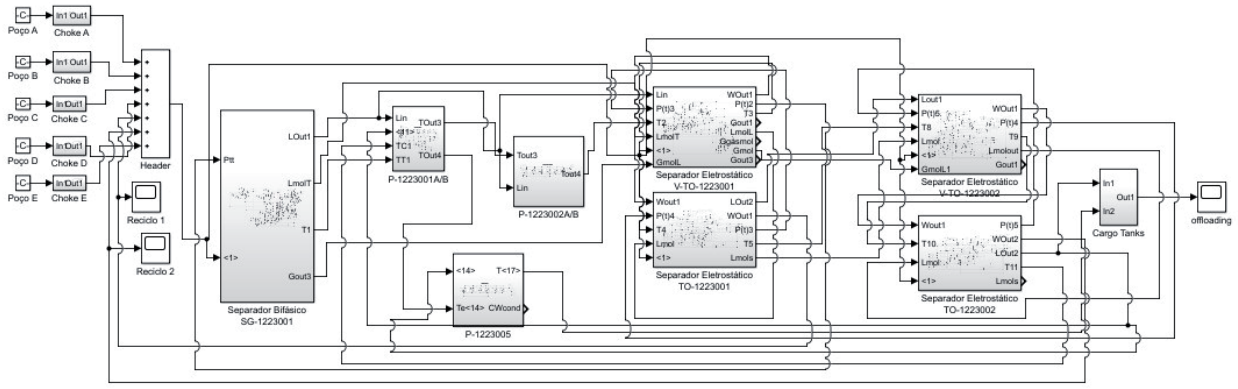

Figure :Simulation of the oil treatment process plant in Simulink®.
Source: Chaves (2021).

L_{in} (t): Volumetric flow of liquid entering the vessel (m³/s);
L_{out} (t): Volumetric flow of liquid leaving the vessel (m³/s);
G_{in} (t): Volume of gas entering the vessel (m³/s);
G_{out} (t): Volume of gas output in the vessel (m³/s);
h_L (t): Height of the liquid to the interphase (m);
P (t): Vessel pressure (bar);
C: Separator length (m);
D: Diameter of the separator (m);
ε: Isentropic expansion factor;
β: Opening dependent (d/D);
K: isentropic exponent;
Z: Compressibility factor.

Next, we can visualize the application of these variables in figures 3 and 4, which show how the relationships are presented in the equipment.

The separator supply does not have a defined model in relation to how much the wells produce depending on the choke opening of each one, as production changes with time, pressure and the arrangement of the wells that produce at that moment, so to solve this problem complex is that the use of neural networks was proposed, given that the fact that they can acquire data and maintain this knowledge to make predictions or identify patterns, is based on the fact that their knowledge units, called artificial neurons, have a large number of interconnections, artificial synapses, which generate information transformation vectors/matrices, (CHAVES, 2021).

Da Silva (2010) presents the main characteristics of ANNs (Artificial Neural Networks): Adaptation by experience, learning capacity, generalization ability, data organization, fault tolerance, distributed storage and ease of prototyping.

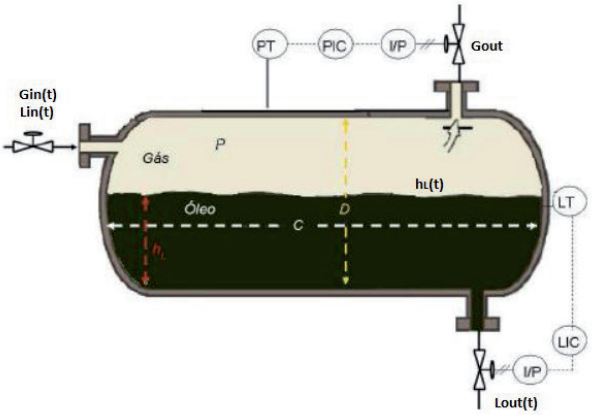

Figure 4: Scheme of variables deduced in the equipment design.
Source: Silva (2013).

There are several possible structures of neural networks, where the main component is the artificial neuron. See figure 5 below for a simplified scheme, where the activation threshold (activation threshold trigger value), "u" which is the activation potential (result of the previous items), "g(.)" called the activation function (filters the output signal) and the output signal "y" which is the value produced by the neuron.

In short, we have the data entry phase (Xn), value weighting (Wn), signal processing (Σ and θ), filtering (u and g(.)) and information provision (y), as shown in figure 5. In this case, for the network input was used the opening of the well valve (choke) and the well pressures and for the outputs the flow of oil and gas produced by the platform was used in order to provide the use of a feedforward network with a backpropagation type algorithm to perform the calculation of the weights and biases necessary for learning the network with an arithmetic error smaller than 10-4. It is worth noting that the network was created with the aim of obtaining results with as few epochs as possible and without underfitting or overfitting in the presentation of data when using the network. For this, a Python language library, PyBrain, was used in the Spyder development environment (IDE). Two neural networks were created to measure the flow of gas and oil from the wells, which were trained from a set of 1200 production data collected in the platform's production information system, with 75% of this data for training and 25% for validation, all taken directly

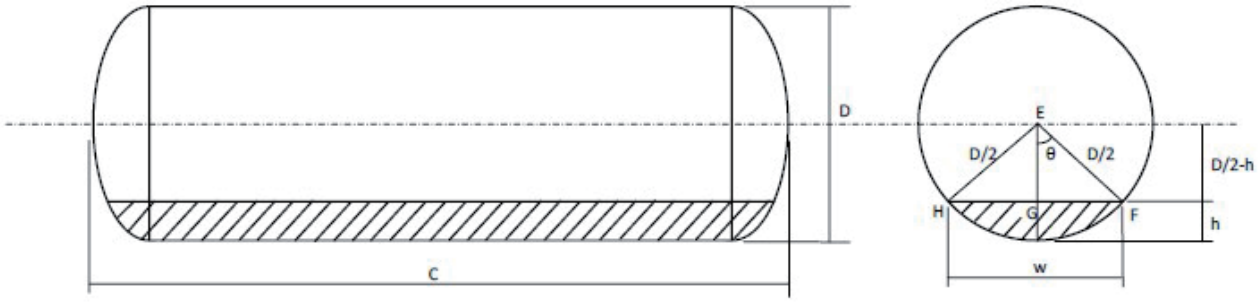

Figure 3: Typical separator dimensions.
Source: De Medeiros (2021).

from the supervisory system of the studied platform, the results and discussions show information such as learning costs and errors used and convergence.

To close the control loop, we need an efficient controller to reduce the error to zero between the setpoint and the measured value regardless of the disturbance that occurs. The conventional PID (Proportional, Integral and Derivative) system is widely used for conventional loops, but in the present study it needs improvement, as the flow control dynamics are complex, as they change with the entry and exit of each well and even with the interaction that occurs with the control of vessel level and pressure. To solve this problem, a Fuzzy-PID controller was designed to reset the error and adapt to the changes that may occur in the behavior of the wells with the process without needing to re-tune. What is the relationship between the degrees of membership and their membership functions, the degree of superposition, the type of defuzzification (C-o-A, C-o-M or M-o-M), the way in which fuzzy learning was carried out, the inference rules and other information that can be achieved? be seen in the results section.

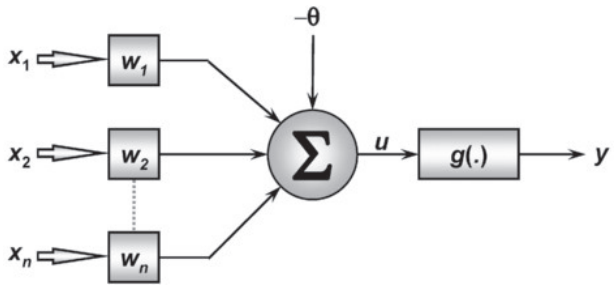

Figure 5: Generic representation of an artificial neuron.
Source: Da Silva (2010).

Results and speeches

As already described, wells produce depending on their head pressure and the opening of the surface control choke valve. As choke opening control is manual and there is still no continuous measurement of individual production per well, a mechanism for measuring the potential of these wells is therefore needed to implement automatic flow control.

There are 5 wells, titled wells A, B, C, D and E, which today alternate to produce the platform's potential, so there are 10 inputs that form the inputs of the neural network, in this case 5 pressure information and 5 information opening of the chokes, a couple of pieces of information for each well. With this we already have the premise of having an input layer of 10 neurons, these neurons being of the linear activation function type, which is recommended when we want to perform data regression in ANN. In the end we have 2 outputs, one for each network, making us arrive at the initial calculation of the intermediate hidden layer of 6 neurons when considering the recommendation that the number of layers in the intermediate layer is the average between the inputs and outputs of a network, Da Silva (2010). With this, we will have an ANN for calculating the oil flow and another for calculating the gas flow according to the topology shown in figure 6. It is worth noting that we preferred to generate two ANNs with one output instead of an ANN with 2 outputs to reduce the number of hidden layers and thus move the problem from the deep learning area to the machine learning universe, a situation that is simpler to work with, since the greater the number of outputs proposed for an ANN, the greater the complexity of the network to predict its behavior using the same set of synaptic weights. The intermediate hidden layer uses sigmoid neurons, those whose activation function uses the sigmoid function, as it manages to provide greater non-linearity to the regression process with the synaptic weights in order to reduce the error more quickly. Functions from the ReLU family were not used, as the input and output data of the network were normalized from 0 to 1, with 1 being the highest value found for that class of data, so there is no point in talking about the negative tail that the functions ReLU and its variations bring gains in the regression, as there are no negative inputs. The linear function was used in the output neuron, as this is what is recommended for regression problems and to improve the accuracy of calculating the weights, a backpropagation algorithm was used, as per (GUALBERTO, 2020). By making variations in the learning rate and moment rate, satisfactory results were achieved for the number of epochs of the networks, with 760 for the oil ANN and 430 for the gas ANN to reach the error criterion of less than 10^{-4}.

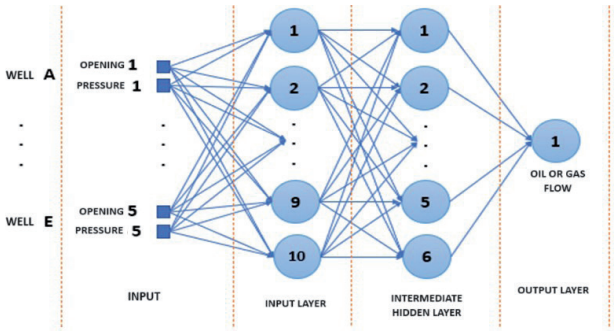

Figure 6: Deployed neural network topology.
Source: Prepared by the author (2022).

Note that the convergence of the gas flow calculation network occurs faster than the oil flow calculation network, this is due to the greater variability of the gas information in relation to the opening of the wells than the liquid information, since The wells produce relative gas flows that are more different than those of oil, which are values closer to each other, making separation difficult. It is also worth noting that the error calculation was made with a test bench that represents 25% of the number of trained samples, which led to an error of 0.0077 for the oil

network and 0.0063 for the gas network, excellent values when compared to what is achieved in practice with other methods, according to (GUALBERTO, 2020).

To ensure that the network created was not overfitting, the graph below was generated, figure 7, which relates the error in predicting the test set with the number of total neurons in the network using dropout. Note that the indicated topology may have the reduction of one neuron in its hidden layer since it presents a smaller test sample set error with 16 neurons than with 17, thus guaranteeing no more overfitting by increasing the error with the reduction of more neurons. Underfitting does not occur given the low error achieved with the network even with more than 40 simulations carried out for evaluation, reaching an average error of 0.00489 for the oil network and 0.00538 for the gas network in the new configuration.

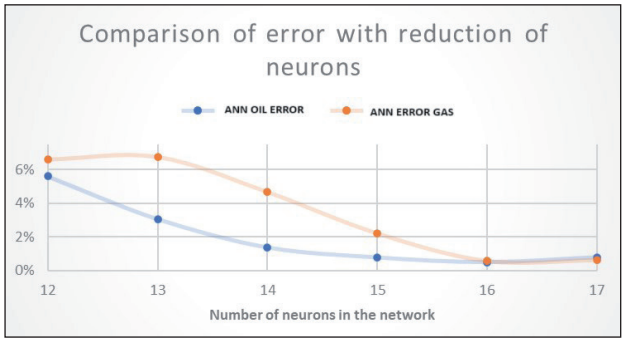

Figure 7: Reduction in the number of neurons as a function of test sample error.
Source: Prepared by the author (2022).

With the optimized network, we can now analyze the oil and gas flow prediction results per well. The networks were used to predict the individual flow per well based on fixing the pressure conditions and choke opening of the wells not targeted for analysis with the variation of the choke opening for the well under analysis within the opening range that had already occurred for the well in practice is considered in the network's training data set, with this procedure being alternated so that each well's flow rate is analyzed depending on its choke opening with the other fixed ones. With this, we obtained good results for this objective for 2 wells, wells A and E, as can be seen in graphs 8 and 9, since these wells have their choke opening data in a good analysis range, from 0 to 100% for well E and 0 to 80% for well A, thus giving a good result for correlation and when compared with practical values, as the profiles shown are close to what is found in production tests for wells in some opening points.

The other 3 wells, wells B, C and D, have little opening data depending on time, where one of them, well D, for example, was only opened up to 13% of its potential, despite the network response data. are coherent up to 13%, we cannot use this information to control within the desired range for this project, thus not focusing on the analysis of these wells and leaving them with a fixed opening.

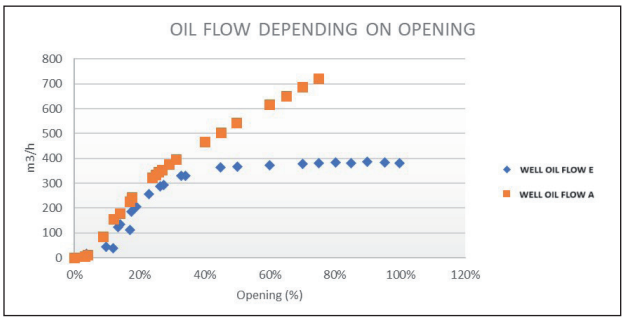

Figure 8: Oil flow from two wells depending on the opening of the choke generated by the oil ANN.
Source: Prepared by the author (2022).

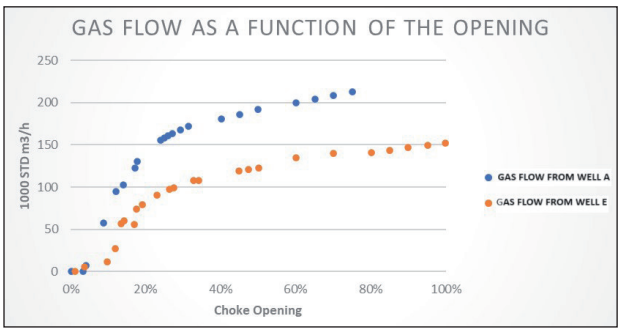

Figure 9: Gas flow from two wells as a function of the opening of the choke generated by the gas ANN.
Source: Prepared by the author (2022).

Figures 10 and 11 show the graphs generated for well D and the discrepancy in the data with reality, given that the network is unable to predict the flow rates for an opening that did not occur in practice and was not part of the network's learning universe, Since the well was only opened up to 13% in reality, it cannot predict values outside this range, the network's prediction only occurs for values within its training range, outside of that they are imprecise and meaningless values.

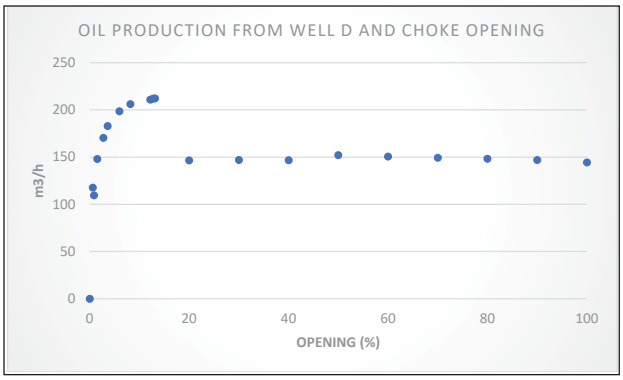

Figure 10: Predicted oil flow from well D depending on the opening of the choke generated by the oil ANN.
Source: Prepared by the author (2022).

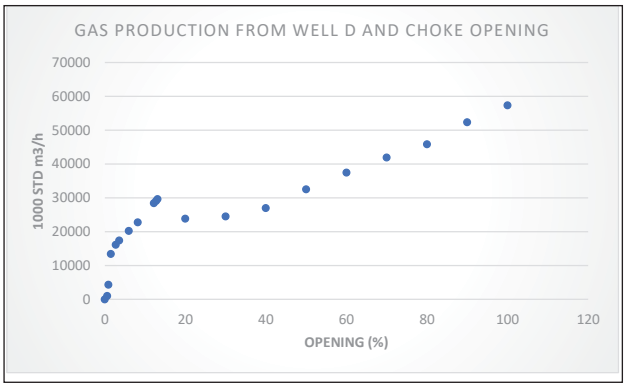

Figure 11: Predicted gas flow from well D depending on the opening of the choke generated by the gas ANN.
Source: Prepared by the author (2022).

With the data presented, it was possible to generate correlations between the opening of the valve and the production of wells A and E in order to use it to control the flow of the platform.

It was also assessed whether the networks used had local minimum and maximum points that generated interpretations different from what was exposed above. For this purpose, 20 tests were carried out with the random initialization of synaptic weights and biases for different moment rates and learning rates to evaluate whether we found different answers and it was seen that the variation between the final data was no more than 7% of those presented here, thus validating that the information was not evaluated on local maximum and minimum points but rather on the global optimum point.

As already stated, marine wells have their openings controlled manually by activating a button that pneumatically opens the well's choke valve and thus increases its flow. As the response to flow variation depends on the operator, we have times when the plant's operating flow is lower than the nominal and as a result there is a loss of production. For this situation, the neuro-fuzzy control logic proposed by this work was created so that within minutes the nominal flow rate of the plant can be recovered regardless of the disturbance or change in the production strategy, or even another desired flow rate, in a safe and secure manner. to minimize losses.

Each point in the plant perceives a disturbance in the incoming flow and reacts in a different way and to a different extent. Therefore, to evaluate the point where the neuro-fuzzy logic will be implemented, a sensitivity analysis was carried out in relation to the liquid flow, as the greater the amplitude, the greater the uncontrollability. For this, 7 points were chosen for sensitivity analysis in order to define where the controlled variable will be read to enable control. See figure 12 for the points analyzed:

With the open loop system, a disturbance was made in the plant's supply current in the form of a positive step of 4%, the results were collected and sensitivity table 1 was prepared.

Table 1: Sensitivity of possible flow control points with Fuzzy-PID control.

Location	Point	Sensitivity
Recycle 1	A	0,156
Recycle 2	B	0,964
Output SG-1223001	C	0,965
Output V-TO-1223001	D	0,929
Output TO-1223001	E	0,918
Output V-TO-1223002	F	0,846
Output TO-1223002	G	0,866

Source: Prepared by the author (2022).

Note that in table 1 the point that is most sensitive to flow variation is the SG output, so if it is controlled by the fuzzy system, then we also have control of the other points, since the other points have lower sensitivity than it and so it will be the point to be used in fuzzy-PID control with neural networks.

It is necessary to use a fuzzy controller because the proposed flow control goes through pressure, level and temperature loops, and interacts with the entire process. Given that this control has complex dynamics, a conventional PID presents difficulty in converging and stabilizing the flow, sometimes even diverging. In order to

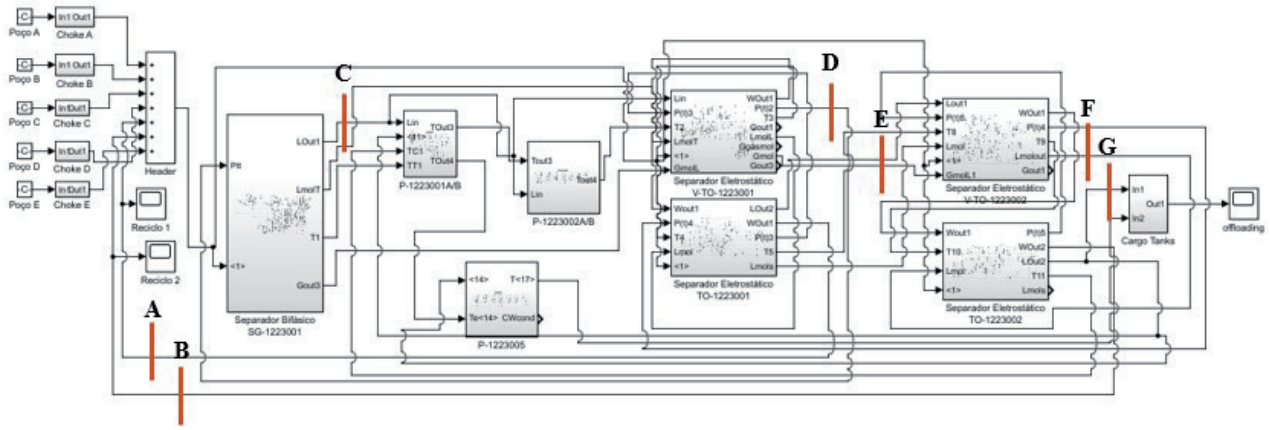

Figure 12: Sensitivity analysis points for installing the Fuzzy-PID Controller with neural networks.
Source: Chaves (2021).

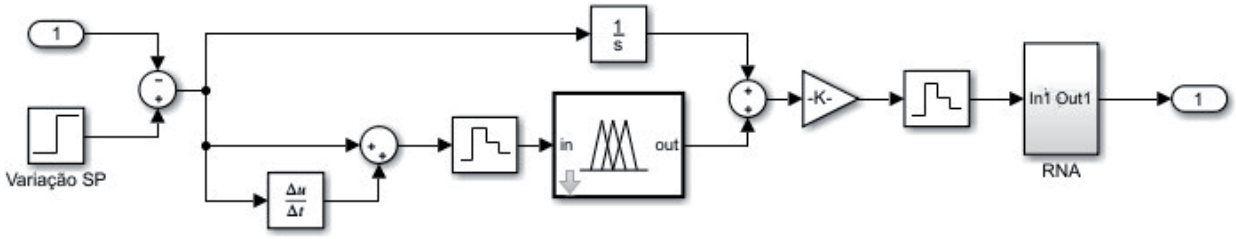

Figure 13: Fuzzy-PID controller with neural networks for flow control.
Source: Prepared by the author (2022).

solve this problem, the scheme in figure 13 was created in Simulink® to control the process.

Note that the controller in figure 13 has as its core a fuzzy controller that represents the possible tuning of PID parameter variations and thus feeds the functions created in neural networks to provide the plant's operating flow. There were several configurations designed for the controller, with the best performance being the configuration of a mamdani controller with two inputs and one output, as shown in figure 14 and with the fuzzification and defuzzification process using sigmoid functions as shown in figure 15.

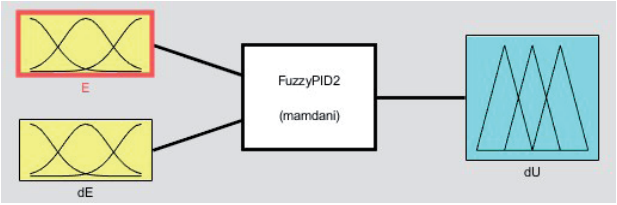

Figure 14: Fuzzy-PID controller schematic in relation to inputs and outputs.
Source: Prepared by the author (2022).

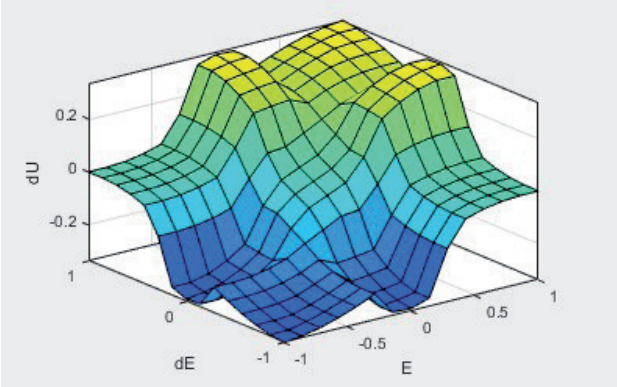

Figure 15: Control surface of the rules imposed for the Fuzzy-PID Controller with neural networks.
Source: Prepared by the author (2022).

The scheme presented above is the one with the best performance among the various simulator schemes where the number of inputs, rules, types of functions (Gaussian, sigmoid, triangular and trapezoidal) and function limit values were varied in the fuzzy controller learning process.

With the scheme ready, simulations were carried out to evaluate performance, making variations in the control setpoint and disturbances in the manipulated variable, in this case being carried out by including a term for reducing well efficiency, simulating a hole in the well column or reduction of the pressure and elevation potential of the well. In figure 16 we can see the controller's response to a 4% increase in the flow setpoint in the 30th minute of the simulation and then in figure 17 we have the reduction in production followed by the controller acting to make the process return to the setpoint of flow even with the drop in well productivity.

It is worth remembering that the gravitational separator is fed in bursts, but for the controller to have a satisfactory response, a filter is used to remove the peak of the burst and make the moving average of the input values in order to obtain a value of less noisy error for the controller.

Note that the result shown in figure 17 brings a lot of gain, as what happens in practice is that there is a delay between the time an operator takes to reduce the efficiency of a well and the adjustment of the valve made by him manually. With the proposed logic, in less than 3 minutes the well is already at a flow rate greater than or equal to the setpoint, whereas in practice, for small variations in production such as the one simulated, it takes hours or even days to adjust, as there is a culture in which the reduction in well efficiency already occurs due to natural decline and is therefore expected.

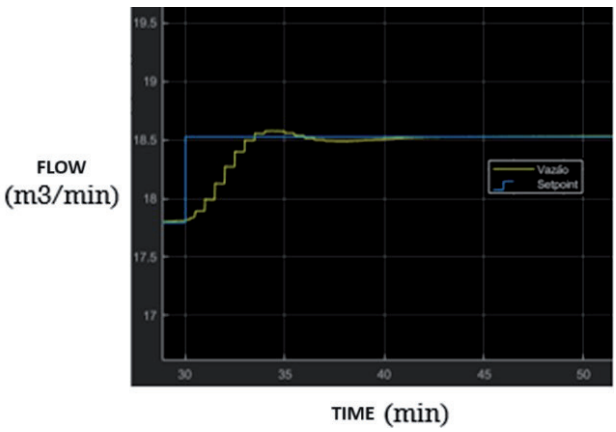

Figure 16: Response of the Fuzzy-PID Controller with neural networks to a variation in the setpoint of 4%.
Source: Prepared by the author (2022).

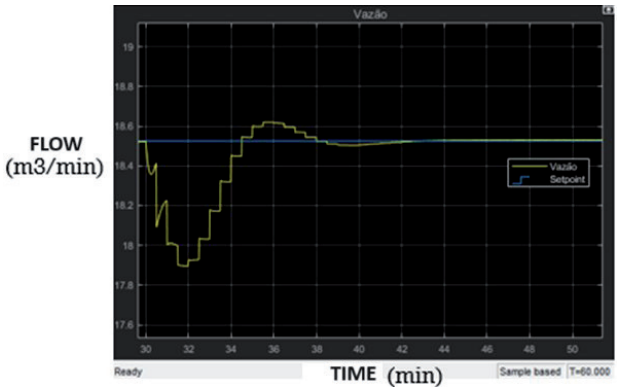

Figure 17: Response of the Fuzzy-PID Controller with neural networks to a 4% drop in productivity.
Source: Prepared by the author (2022).

In order to evaluate whether the control could be done in a simplified way by a conventional PID controller, it was seen that the control was sufficient for the servo mode, but it was not capable of performing the control in the regulatory mode satisfactorily, as in the case under analysis The variable that suffers the disturbance is the well's own production function and, therefore, for the PID to operate, a new tune would be necessary, as the dynamics of the process are altered. Below is a comparison between the implemented Fuzzy-PID control and the conventional PID by performance indicators using well A to control the plant flow and measuring the output flow at the exit of the gravitational separator.

Table 2: PID control performance comparison versus Fuzzy-PID control.

Ajuste de resposta em malha aberta	Sintonizado por	Modo	IAE	ISE	ITAE	ITSE	CE
PID por Sundaresan e Krishnaswamy	IMC $\tau_C=\tau/10$	Servo	3,74	1,12	22,38	8,92	0,038
Fuzzy-PID poço A	Função sigmoide	Servo	1,68	0,717	12,88	4,26	0,018

Source: Prepared by the author (2022).

See that the Fuzzy-PID performs better than the conventional PID for a setpoint change of 4% in the required production flow through the process, in the same way as Carvalho (2020, p. 2) stated in his work. Furthermore, the Fuzzy-PID also controlled for regulatory mode without the need for new tuning, while the conventional PID did not converge with the tuning that was for servo mode in regulatory mode.

Table 3: Performance comparison of PID control versus Fuzzy-PID control.

Ajuste de resposta em malha aberta	Sintonizado por	Modo	IAE	ISE	ITAE	ITSE	CE
Fuzzy-PID poço A	Função sigmoide	Regulatório	5,55	3,29	26,2	12,08	0,029

Source: Prepared by the author (2022).

Another advantage of Fuzzy-PID control in relation to PID is that it is possible to change the well under control, in the case of well A to well E, and still continue to automatically control the process without the need for new tuning, meanwhile the PID does not work without retuning. See below the flow correction graph in servo mode for well E, maintaining all the same conditions imposed for the control simulation with well A presented above and the convergence to its setpoint.

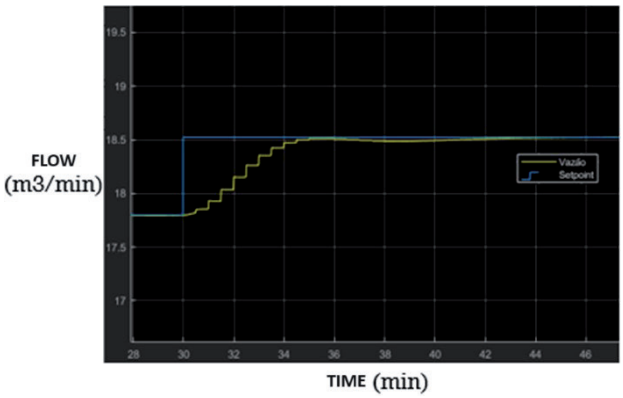

Figure 18: Fuzzy-PID Controller response with neural networks to setpoint variation of 4% for well E.
Source: Prepared by the author (2022).

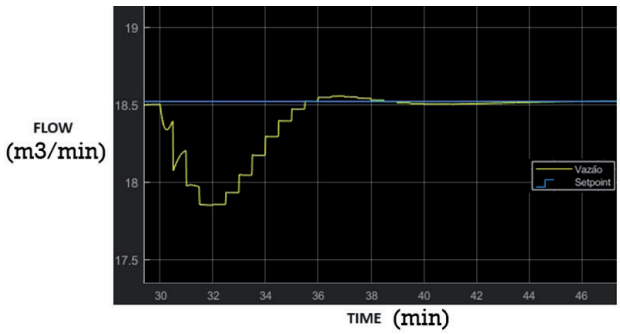

Figure 19: Response of the Fuzzy-PID Controller with neural networks to a 4% drop in productivity for well E.
Source: Prepared by the author (2022).

See table 4 for a comparison of control performance for the same conditions, just by changing the well. In the simulations for well E, the actuator works harder, not because of the controller's inefficiency, as in regulatory mode the IAE and ISE are smaller and the rest of the indicators are very close in servo mode, but rather due to the fact that well E has lower productivity, thus requiring a larger opening to obtain the same setpoint flow.

Table 4: Fuzzy-PID control performance comparison Well A versus Well E.

Ajuste de resposta em malha aberta	Sintonizado por	Modo	IAE	ISE	ITAE	ITSE	CE
Fuzzy-PID poço A	Função sigmoide	Servo	1,68	0,717	12,88	4,26	0,018
Fuzzy-PID poço A	Função sigmoide	Regulatório	5,55	3,29	26,2	12,08	0,029
Fuzzy-PID poço E	Função sigmoide	Servo	2,02	0,9138	15,94	5,62	0,039
Fuzzy-PID poço E	Função sigmoide	Regulatório	2,47	1,07	19,5	7,71	0,041

Source: Prepared by the author (2022).

At the end, an assessment was made of the financial gain with the application of the technology in the studied FPSO and since the implementation of the neuro-fuzzy flow control logic allows the plant to always work at the setpoint flow rate when in closed loop, thus generating a gain related to the difference in production carried out in this way, in certain periods of time, in relation to what is produced during the time in which the plant does not operate in its nominal condition due to waiting for the operator's reaction time to increase the flow rate of the wells, that today operate without automatic control, when there is a reduction in efficiency or disturbance in the process and that require manual action from the operator.

Note that the difference in production between the two methods depends on the plant operator and the moment in which the reduction in efficiency occurs, so an average monthly gain of 25.6 m3 of oil was calculated between the time the neuro-fuzzy control was active. and the operator's reaction time, when analyzing the platform's production of the last 2 years when accounting for production vouchers below nominal production and which could be corrected by the proposed system.

With the data above, with the current oil price at 87.51 U$$/bbl and the dollar at 5.46 R$/ U$$, using an internal rate of return or attractiveness of 10% p.a, considering that Petrobras has 72 platforms in similar production conditions that can undergo the same optimization and that Petrobras' current business plan is for 5 years ranging from 2022 to 2026, it was possible to calculate the gain of R$ 923.256.09 financial return for 1 platform per year and up to R$277.189.464.08 in EVA delta for 72 platforms considering the company's 2022-2026 business plan.

Conclusions

As shown in the results, the neural network created was of the feedforward type with a backpropagation weight calculation algorithm and used an optimized architecture after studying the dropout of an input layer with 10 neurons (with linear activation function), a intermediate of 5 neurons (with sigmoid activation function) and an output of 1 neuron (with linear activation function), totaling 16 neurons. The optimal moment term and learning rate for network convergence were 0.6 and 0.4, respectively, and no local maxima and minima were found that would significantly alter the network's final error for this architecture. It is worth noting that with the ANN created it was possible to predict the behavior of the wells in real operating conditions with good accuracy, however it was not possible to observe the flow rate for opening parameters outside the network training sample space with good accuracy.

With the studies carried out, it was possible to implement a fuzzy-PID controller to act on the correlation generated by neural networks and thus obtain a flow controller for the closed-loop process. It is worth noting that the Fuzzy-PID with the response surface created has good tuning for different flow rates and even for changing conditions in the dynamics of the wells.

It is suggested that the work carried out here is also carried out in CFD (Computational Fluid Dynamics) in order to improve the accuracy of the models and controls and thus obtain an optimization as close as possible to reality in terms of financial results.

It is considered that the objective of the research has been achieved and that the development of more work in this area and with the tools proposed here can bring further advances to the industry and to scholars in the area.

References

1. **Bello, Opeyemi** *et al. Application of artificial intelligence techniques in drilling system design and operations: a state of the art review and future research pathways.* In: SPE Nigeria Annual International Conference and Exhibition. OnePetro, 2016.
2. **Campos, Mario CMM et al**. *Intelligent system for start-up and anti-slug control of a petroleum offshore platform*. **In: OTC Brasil. OnePetro, 2017.**
3. **Carvalho, Adelson S; Almeida, Gabriel CS; Salles, Rafael S.** *Implementação de Controladores Híbridos PID-Fuzzy: Análise de Desempenho em uma Planta de Nível*. In: Congresso Brasileiro de Automática-CBA. 2020.
4. **Chaves, José Andersands Flauzino; Da Silva, Flávio Vasconcelos; Fonseca, Rodolpho Rodrigues**. *Modelagem e simulação dinâmica do processo de tratamento de óleo em um FPSO*. Apresentação de trabalho. III Seminário de Pesquisa em Engenharia Química. Universidade de Federal de Sergipe. 2021.
5. **Costa, Susiane Marques.** *A exploração do pré-sal e o futuro brasileiro.* **Trabalho de conclusão de curso. UNB. 2014.**
6. **Crivellari, Gabriel Pereira**. *Modelagem matemática e simulação de um permeador de gases para separação de CO2 de gás natural.* Tese de Doutorado. Universidade de São Paulo. 2016.

7. **Da Silva, Ivan Nunes; Spatti, Danilo Hernane; Flauzino, Rogério Andrade.** *Redes neurais artificiais para engenharia e ciências aplicadas-curso prático.* São Paulo: Artliber, 2010.
8. **De Medeiros, Márcio Lindemberg Bezerra; De Oliveira Junior, Antonio Martins; Fonseca, Rodolpho Rodrigues.** *Gain scheduling control applied to oil and gas separator level loop.* Research, Society and Development, v. 10, n. 4, p. e55010414397-e55010414397, 2021.
9. **Gualberto, Arnaldo.** *Manual Prático do Deep Learning - Redes Neurais Profundas.* Machine Learning Analyst at Wildlife Studios. 2020.
10. **Nunes, Giovani Cavalcanti; De Medeiros, José Luiz; Araújo, Ofélia de Queiroz Fernandes.** *Modelagem e controle da produção de petróleo: aplicações em Matlab.* Editora Blucher, 2010.
11. **Silva, Filipe Reolon da.** *Estudo de um novo sistema de separação primária de gás-óleo-água para plataformas de petróleo.* Trabalho de conclusão de curso. Universidade Federal do Rio Grande do Sul. 2013.
12. **Torres Campos, Orlando.** *La internet industrial de las cosas & la inteligencia artificial, el impacto en la economía y las oportunidades de nuevos negocios.* Revista CIES Escolme, v. 11, n. 2, p. 127-139, 2020.