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Artificial Intelligence and Digital Twin for Effective Risk Management in an experimental plant

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Abstract

The Oil & Gas industry is on the threshold of digital transformation through integrating Digital Twins and Artificial Intelligence. However, the widespread adoption of this technology is still limited. This study introduces an innovative use of Digital Twins based on models obtained through artificial intelligence to analyse a vertical tank behaviour of an experimental plant. Moving beyond the traditional non-real-time analysis software that currently dominates plant operations, this approach leverages real-time data to advance the modelling process. From the previous research about using artificial neural networks to model an ejector, the present work expands the scope to include the vertical reservoir. It adds a new piece to constructing a system that can correctly describe the experimental plant and detect its anomalies. The tank model is realised through two artificial intelligence algorithms that accurately predict pressures and water levels inside the tank at the "t+1" time step. These algorithms have been rigorously trained and tested with real plant data, demonstrating high fidelity in modelling tank behaviour with an accuracy of 99.98% and 99.75%. With this experimental case, the synergy between Artificial Intelligence and Digital Twins demonstrates its relevance in real-time Oil & Gas plant management. It underscores the potential for transformation to enable more dynamic, resilient, effective and safe plant operations.

Keywords: Energy Sector; Virtual Models; Intelligent Systems; Artificial Intelligence Techniques; Dynamic Plant Management

1. Introduction

Industrial plants comprise complex systems where advanced technological elements interact seamlessly. The growing integration of digital solutions, such as Cyber-Physical Systems (CPSs), within modern industrial setups (Ina Lidere & Lektauers, 2023) enhances operational efficiency and functionality (Institute of Standards, 2014). The digital transformation is revolutionising all sectors (Pierluigi Sandonnini, 2022; Wanasinghe et al., 2020), including the Oil and Gas sector, driven by advancements in Industry 4.0, incorporating technologies such as IoT, Big Data, and AI (Elijah et al., 2021). However, this digitalisation introduces vulnerabilities, necessitating thorough investigations into potential system failures within the cyber-physical realm. To achieve this, detailed performance evaluations must be conducted within simulated environments, enabling the exploration of hypothetical scenarios without real-world disruptions. These simulations rely on Digital Twins (DTs) to ensure accurate mirroring of cyber-physical assets (Zipper & Diedrich, 2019). DTs represent asset and process states, accounting for potential changes in behaviour caused by technical malfunctions, natural disasters, or human-induced damages, whether intentional or accidental. Failures within industrial systems can significantly degrade plant performance and result in many consequences, spanning economic losses to safety, security, and environmental risks. Therefore, comprehensive system performance assessments are imperative, facilitated by simulated environments where hypothetical scenarios can be explored without real-world repercussions. Plant simulations leverage Digital Twins to maintain accurate reflections of cyber-physical assets (Zipper & Diedrich, 2019). These representations depict the state of assets and processes, considering factors such as ageing, faults, and wear that occur over time. This paper is a follow-up to the previous work on the construction of a Digital Twin of an experimental Oil & Gas plant (Pietrangeli et al., 2023) related to an ejector modelling to estimate some performance and criticalities of the system. This paper focuses on modelling another component of the same plant: the vertical tank. In this case, the model will be realised through Artificial Intelligence (AI) algorithms that can predict the characteristic parameters of the studied plant elements, such as internal tank pressure and water tank level, at the next step. This paper differs from the previous one in the element to be modelled, especially, in how it is modelled: it was decided to include a newly emerging tool such as artificial intelligence. In this context, the DT emerges as a transformative technology, optimising asset management and expanding operational and strategic benefits (Elijah et al., 2021; Pietrangeli et al., 2023). Specifically, in Section 2 a brief literature review will be reported; in Section 3, a panoramic view of the experimental setup will be given, specifically dealing with the vertical tank and the acquisition system; Section 3 will present the general elements regarding modelling by briefly describing the type of AI algorithm; Section 4 will give all the specific information about the two algorithms with the results obtained; finally, the discussion and conclusion.

2. A short literature review

Digital Twins have become a cornerstone in complex systems engineering and management (Alimam et al., 2023; Ina Lidere & Lektauers, 2023). A DT is a digital replica of a physical asset, process, or system that enables real-time simulation, analysis, and optimisation of operations (Lanzini et al., 2023). This technology can range from simple static models to sophisticated dynamic representations that update and change with their physical counterparts. DTs are particularly valuable in the Oil & Gas industry due to the complexity and risks associated with operations. They simulate drilling, production, and logistics processes, enabling companies to anticipate problems, optimise performance and improve predictive maintenance. For instance, through Digital Twin models, the status of oil rigs, subsea pipelines and other critical infrastructure can be monitored in real-time, thereby reducing downtime and increasing safety (Mendoza et al.; Wishnow et al., 2019). The integration of AI into DTs has marked another step forward in the ability of these models to predict failures and optimise processes without direct human intervention. AI enables DTs to analyse large amounts of operational data in real-time, continuously learning and adapting to offer increasingly accurate predictions (Elijah et al., 2021). This fusion of AI and DT can become crucial for companies seeking to remain competitive in a globalised and technologically advanced market (Wishnow et al., 2019). Advances in this field continue to push the boundaries of technology and reconfigure expectations of what is possible in monitoring, maintaining, and operating industrial infrastructure globally (Ahmed Soomro et al., 2024). From the literature, it is already possible to understand that the combination of DT and AI in the Oil & Gas sector is not that common. In fact, by performing a search on Scopus with the key " *"digital twin*" AND "artificial intelligence" AND "oil and gas"* ", 46 articles can be identified. As expected, all the articles were published over the past 6 years, as seen in Figure 1. The combination of AI and DTs has garnered increasing interest in recent years.

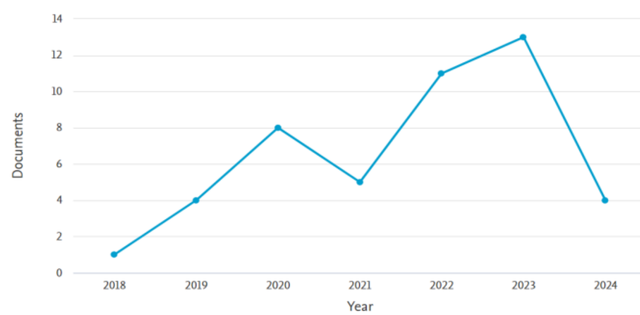

Figure 1. Documents per year – Scopus

As shown in Figure 2, the fields involved in this theme are diverse and range from the area of "Engineering" (23.5%) to "Energy" (20.6%), "Computer Science" (12.7%), "Earth and Planet" (15.7%), "Materials Science" (5.9%), etc. To focus the search more on the industry, a filter was applied that limited the search to the engineering subject area. Therefore, the number of articles was reduced to 24.

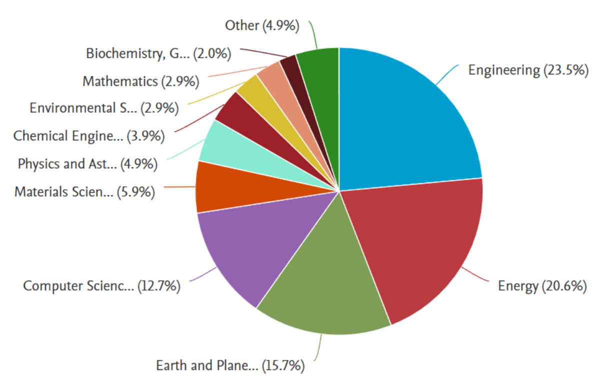

Figure 2. Documents by subject area -Scopus

From a reading of the articles abstracts it was possible to exclude those related to the construction and civil engineering sector, focusing on the related to the industrial engineering field. Thus, 11 articles were analysed in Table 1 and ranked according to the presence (the number of "•" represents the degree of presence) of a description of DT elements, AI algorithms, and listing other similar strategies mentioned.

Table 1. Literature review

Ref.	DT	AI	Other technologies cited
(Poddar, 2018)	•••	•••	-
(Wishnow et al., 2019)	••	•	- Aerial Data Gathering & Interpretation - Machine & Deep Learning - Natural Language Processing - Quantum Computing - 3D Printing
(Elijah et al., 2021)	••	••	- IIoT - Big Data Analytics - Cloud computing - AM - Augmented Reality - Cyber-Physical System
(Mendoza et al., 2021)	••	••	- ASPEN HYSYS
(Yusupbekov et al., 2022)	•••	••	-
(Ma et al., 2022)	•••	••	-
(Alimam et al., 2023)	•••	••	- Augmented Reality - ML
(Chelliah et al., 2023)	-	••	- ML - Deep Learning algorithms - Computer Vision - Natural Language Processing - Industrial Internet of Things - Cyber-Physical Systems - 5G communication, - Event-Driven Architecture - Micro-Services Architecture
(Ahmed Soomro et al., 2024)	•	•••	- ML - ANNs - Support Vector Machine (SVM) - Decision tree - Random forest - Gradient boosting
(Camara Dit Pinto et al., 2024)	••	••	-
(Pietrangeli et al., 2023)	•••	-	- ANNs

Most of these articles are literature reviews investigating the potentialities of AI-integrated DTs, and the main aspects emphasised are the possibility of reducing costs, waste, and risks associated with the Oil & Gas system, etc., due to the presence of AI algorithms based and trained on the real and truthful data of the system itself (Ahmed Soomro et al., 2024; Elijah et al., 2021; Mendoza et al., 2021). The construction of Digital Twins whose models are realised by exploiting AI and real data, makes it possible to better grasp the specific characteristics of a certain plant while also favouring its resilience: as initially introduced by Holling (1973), resilience in industrial settings can be defined as the ability to anticipate, absorb, adapt and recover from a disruptive event (Patriarca et al., 2018) and plants' resilience implies being able of monitoring systems operations and running strategies to facilitate the system's response against known and unknown hazards and disturbances. Introducing new technologies in the context of DT certainly, such as AI, new types of communications and connections, etc., ensures resilience and a faster and more effective response capacity to any risk (Luis et al., 2021). Still, it confronts us with a greater risk, which is that of cyber-attacks. Once the entire DT has been constructed and all the external connections have been enabled, assessing its resistance and resilience to this type of increasingly widespread phenomena will be necessary. Here, an application of AI algorithms has been reported for the development of a model of the plant's vertical tank; the algorithms will be used in the context of the Digital Twin of the entire plant.

3. Materials and Methods

This work is closely related to the work reported in this article (Pietrangeli et al., 2023), where the realisation of the ejector model for the Digital Twin of the plant was presented. The ejector is an instrument upstream of the vertical tank that, in the context of the DT of the whole system, provides values at t instant that are then used by the tank model to predict the internal tank pressure value of instant *t+1*. Both models will be used in the final DT, which will be able to provide a real-time representation of the state of the experimental plant. The experimental plant, the vertical tank and the acquisition system will be described below.

3.1. The experimental plant

The facility in focus is an experimental plant located within the laboratories of the Department of Industrial Engineering and Mathematical Sciences (DIISM) of the Polytechnic University of Marche. Originally built in the 1990s, the main objective of this facility was to study the operation of one of the most common methods of extracting oil from inactive wells. To avoid the high costs associated with installing pumps at the bottom of the reservoir whose internal pressure does not guarantee a natural surfacing of oil and gas, a technique was developed that exploits an ejector using the pressure of an adjacent active well (Figure 3). The operation of this extraction method is reproduced by taking advantage of the UNIVPM experimental plant. The experimental system uses water and air instead of oil and gas for safety. This system configuration is shown in Figure 4.

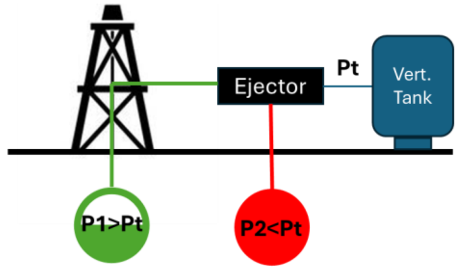

Figure 3. Scheme of extraction plant

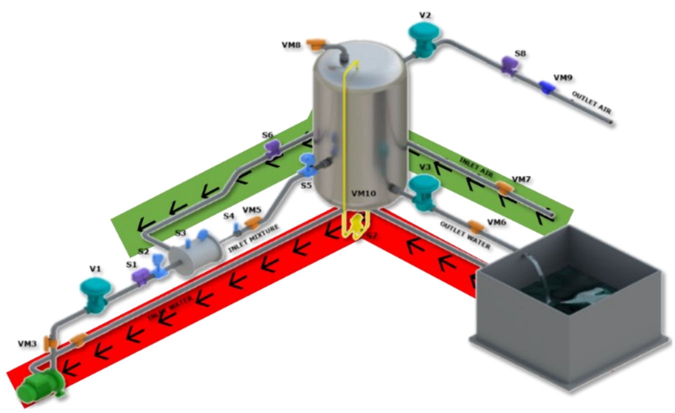

Figure 4. Plant scheme

The starting point is an open water tank; water is pumped from this tank (in green in Figure 4) to the ejector, which blends with air, forming a two-phase mixture. This mixture is then directed to a vertical tank that acts as a separator, allowing the air to be expelled back into the open tank through a special channel. Throughout the system, there are three electro valves (coloured in turquoise), eight sensors (coloured in light blue) and manual valves (coloured in orange) strategically placed to facilitate the simulation of system failures. Manual valves have been inserted physically but in a controlled manner to simulate anomalies, such as blockages, that may occur in the real system. These manual valves can be closed in such a way as to realise three levels of anomalies: 100% opening (closure) defined at steady state; above 67% opening (closure) corresponds to anomaly level 1; above 34% anomaly level 2; and 0% opening (closure) anomaly level 3. More details will be provided in Section 2.2. In the experimental plant, the inlet air channel represents the real inactive oil well while the inlet water channel (from the open reservoir to the pump) represents the active well; the ejector plays the same role while the vertical reservoir represents the collection point of gas and oil where the two fluids separate and are then collected separately. Figure 4 shows the elements representing the active and inactive wells with the same colours as in Figure 3.

Figure 5. The experimental plant

Table 2. PID values

Value	PID 1 - V1	Pid 2 - V2	PID 3 - V3
Setpoint	4.437 [mA]	9.556 [mA]	12.813 [mA]
k_p	1	1.7	0.8
k_i	0.7	0.7	0.4
k_d	0	0.1	0

Figure 5 shows pictures of the actual experimental facility in the DIISM laboratories. Table 3 and Table 4 show the characteristics of each sensor and electro-valves in the system. As shown in Table 3, the sensors acquire several variables that will then be reported in the dataset with their units of measurement; Table 2, on the other hand, shows the characteristics of the 3 solenoid valves that are controlled by a PID system that adjusts their openings and closings based on the values recorded in the system. The parameters characterising the PID are kp, ki and kd and are specified for each electro-valve (Table 2).

Table 3. Sensors

ID	Description	UM	Type	Tag
S1	Inlet water pressure	[bar]	OUTPUT	Endress+ Hauser Cerabar M PMP51
S2	Inlet water flow rate	[m^3/h]	OUTPUT	Endress+ Hauser Promag W
S3	Ejector pressure	[bar]	OUTPUT	Setra 280E
S4	Mixture pressure in the diffuser	[bar]	OUTPUT	Foxboro 841GM CI1
S5	Tank pressure	[bar]	OUTPUT	Foxboro 841GM0CI1
S6	Inlet air flow rate	[m^3/h]	OUTPUT	Foxboro Vortez DN 50
S7	Water level in the tank	[mm]	OUTPUT	Foxboro IDP010
S8	Air flow rate at the outlet	[m^3/h]	OUTPUT	Endress+ Hauser Prowirl 200

Table 4. Electro-valves

ID	Description	UM	Type
V1	Valve 1 closure	[%]	INPUT
V2	Valve 2 closure	[%]	INPUT
V3	Valve 3 closure	[%]	INPUT

3.1.1. The vertical tank

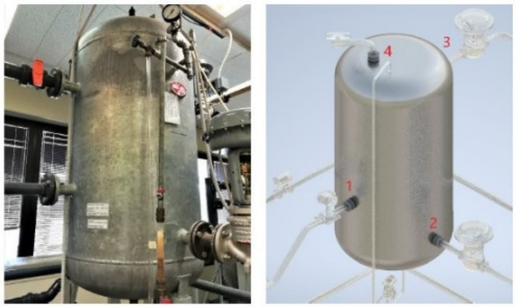

Figure 6. Vertical Tank

The vertical tank (Figure 6) allows the storage of pressurised water and performs the vertical separator task. This device is generally made of galvanised steel in a hot bath, such as the one studied in this article, or, alternatively, with stainless steel. The tank under consideration has an access point (1) for the two-phase fluid exiting the ejector, an outlet channel for the liquid component (2), and an outlet point for the gaseous part of the incoming mixture (3). According to regulations, a spring-loaded safety valve is set at a pressure 10% lower than the maximum allowable pressure.

Table 5. Vertical tank - specification

ID	Description
Model	Elbi 780-l
Capacity	780 l
Maximum pressure	9.8 bar
Operating temperature	-10° to +50° C
Material	Galvanized Steel

3.2. Acquisition system and dataset

All sensors and solenoid valves on the plant are physically connected to a device called Revolution Pi (RevPi). Revolution Pi is an open, modular, low-cost industrial PC based on the well-known Raspberry Pi. Housed in a slim DIN rail housing, the three available base modules can seamlessly expand with various I/O modules and fieldbus gateways (Revolution Pi Products - Industrial Raspberry Pi). This device collects and transmits data via Ethernet to a dedicated plant interface. The User Interface (UI) interface developed is shown in Figure 7. The UI has a CAD model on which it is possible to display the flow of water, the graphs relating to the measured variables (Table 3), the section dedicated to the PID in which you can also set the additive, derivative and proportional constants, a section devoted to the manual valves and a section to record the values collected from the moment of starting the recording until its stop. Through this last section, it was possible to collect the data relating to the plant. The dataset was acquired by recording the table variables for about 3 minutes by changing the openings/closures of the 7 manual valves. From the dataset acquired by the sensors on the system, only the values of the water flow inlet and airflow inlet in the tank, as well as the internal tank pressure and the water level, are extracted. The parameters related to the 7 manual valves are collected by the operator recording the specific UI test. The dataset for training the AI algorithm is reconstructed by entering the pressure and level data related to the tank at instant t, values for manual valves (variable from 0 to 3 depending on the degree of closure/ level of anomaly, explained in Table 6), and pressure and levels data at the instant t+1.

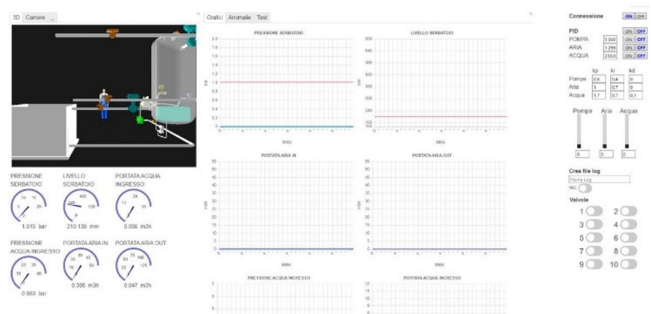

Figure 7. Experimental plant – user interface

Table 6. Manual Valves - Anomalies levels

	VM Normally opened	VM Normally closed
	VM3 ,VM5, VM6, VM7, VM9	VM8 ,VM10
0	0% closed = rotation of 0°	0% opened = rotation of 0°
1	33,3% closed = rotation of 30°	33,3% opened = rotation of 30°
2	66,6% closed = rotation of 60°	66,6% opened = rotation of 60°
3	100% closed = rotation of 90 °	100% opened = rotation of 90 °

Table 7. Dataset for the AI algorithms

N°	QairIN(t)	QwatIN(t)	Ps(t)	Ls(t)	Ps(t+1)	Ls(t+1)	VM3	VM5	VM6	VM7	VM8	VM9	VM10	V2	V3
1	QairIN(t) – air flow rate at the tank inlet	Qwatin(t) – water flow rate at the tank inlet	ps1	ls1	ps2	ls2	0	0	0	0	0	0	0	The value assumed by the electro valves V2 and V3 are established by the PID control and are expressed in the percentage of opening.	
2			ps2	ls2	ps3	ls3	1	0	0	0	0	0	0		
3			ps3	ls3	ps4	ls4	2	0	0	0	0	0	0		
4			ps4	ls4	ps5	ls5	3	0	0	0	0	0	0		
5			ps5	ls5	ps6	ls6	0	1	0	0	0	0	0		
6			ps6	ls6	ps7	ls7	0	2	0	0	0	0	0		
7			ps7	ls7	ps8	ls8	0	3	0	0	0	0	0		
8			ps8	ls8	ps9	ls9	0	0	1	0	0	0	0		
9			ps9	ls9	ps10	ls10	0	0	2	0	0	0	0		

10	ps10	ls10	ps11	ls11	0	0	3	0	0	0	0
11	ps11	ls11	ps12	ls12	0	0	0	1	0	0	0
12	ps12	ls12	ps13	ls13	0	0	0	2	0	0	0
13	ps13	ls13	ps14	ls14	0	0	0	3	0	0	0
14	ps14	ls14	ps15	ls15	0	0	0	0	1	0	0
15	ps15	ls15	ps16	ls16	0	0	0	0	2	0	0
16	ps16	ls16	ps17	ls17	0	0	0	0	3	0	0
17	ps17	ls17	ps18	ls18	0	0	0	0	0	1	0
18	ps18	ls18	ps19	ls19	0	0	0	0	0	2	0
19	ps19	ls19	ps20	ls20	0	0	0	0	0	3	0
20	ps20	ls20	ps21	ls21	0	0	0	0	0	0	1
21	ps21	ls21	ps22	ls22	0	0	0	0	0	0	2
22	ps22	ls22	ps23	ls23	0	0	0	0	0	0	3

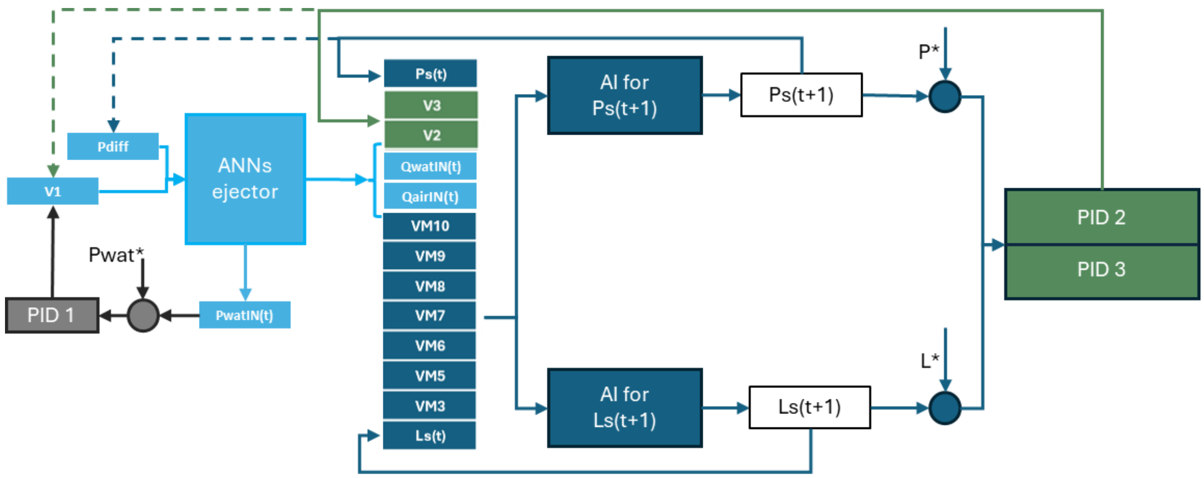

Figure 8. ANNs model of the ejector (light blue), AI-model of the tank (blue), PID 2 and PID 3 controller (green), PID 1 controller (gray)

4. Artificial Intelligence algorithms

As already pointed out in the previous work (Pietrangeli et al., 2023), today, the models of the elements used in the Oil & Gas plants are almost carried out with specific software (also not open sources) that mainly performs thermos-dynamic and/or fluid-dynamic analyses. In addition, it is impossible to analyse a system completely using a single platform or a single technology, but it is necessary to use multiple software and devices that must communicate and collaborate, with all its attendant difficulties. The best alternative in this context, proposed also in this article, is the construction of a DT of the system. Modelling all parts of the plant provides a tool to analyse, simulate and control the plant in real-time. As mentioned above, the ejector model was realised and explained in a previous work (Pietrangeli et al., 2023) and exploited artificial neural networks to estimate the flow rate of water from the air and the pressure of the ejector. In this case, the vertical reservoir behaviour model is developed using two artificial intelligence algorithms developed in Python with the same structure. These two algorithms will take information about the air and water flow rate from the ejector model. Then, they will be used in the PID control system for punctual adjustment of the parameters of interest by the electro-valves, as shown in Figure 8. With this model connected to the PID system, online or offline analysis, simulations and tests can be carried out without incurring any possible system damage or danger.

5. The applied model

To predict the value of pressure and level at time t+1, we used two artificial intelligence algorithms that take the same input parameters. The two AI algorithms are of supervised type and are schematised in Figure 9.

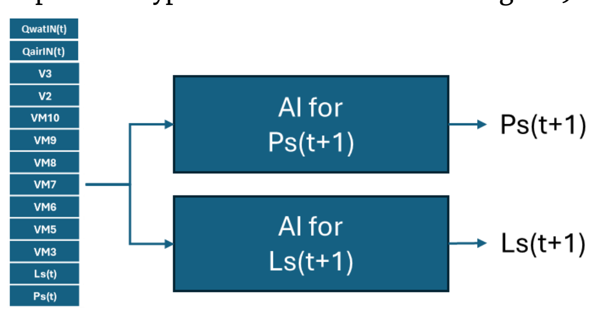

Figure 9. AI algorithms

Both AI algorithms have the same structure: the algorithm that goes into the model is implemented through the sklearn library in Python. The model is specifically a DecisionTreeRegressor, which is used to predict the value of a target variable Ps(t+1) and Ls(t+1) based on a set of other variables (features) extracted from the dataset loaded via an Excel file (dataset as presented in Table 7). The code was built by first implementing a section for loading data. The data is stored in a pandas DataFrame. From this pandas.DataFrame, the columns Ps(t), Ls(t), QairIN(t), QwatIN(t), VM3, VM5, VM6, VM7, VM8, VM9, VM10, V2 and V3 are then selected and assigned to the independent variable X while the column Ps(t+1) and the column Ls(t+1) become the dependent variable y respectively of the AI algorithms for predicting the pressure and level at the next instant. The dataset is divided into training and test sets with train_test_split, keeping 20% of the data for testing and using a random_state of 42 to ensure reproducibility. A DecisionTreeRegressor with random_state=42 is instantiated to ensure consistency across runs. No parameters are specified, such as maximum tree depth (max_depth), minimum number of samples per leaf (min_samples_leaf), etc., so the model will use the default values. The model is then trained on the training data (X_train, y_train) and is first tested on the (X_test, y_test) data. The coefficient of determination R^2 is used to evaluate the model's performance on the test data. The value of r2_score indicates how well the model predicts the target compared with the target mean. The Root Mean Square Error (RMSE) between the predicted and actual values is also calculated, measuring the prediction error in absolute terms. The two algorithms realised in this way allow to predict the values of the internal tank pressure and the tank level with scores of 99.91% and 99.71%, respectively, and therefore, the average square error committed will be 0.00336 bar and 2.70 mm, respectively. Hyperparameterization could be useful in optimising model performance using a scikit-learn Decision Tree Regressor type algorithm, so it was decided to evaluate it at the end of the algorithms that already reach a good score. The hyperparameters that were analysed are the criterion, the maximum tree depth (max_depth), the minimum number of samples needed to subdivide a node (max_leaf_nodes), and the minimum number of samples in a leaf (min_samples_leaf). To do this, sklearn's GridSearchCV search grid was applied. For the parameters entered in the GridSearcCV and reported in Table 8, the algorithm for tank pressure prediction obtained better results (even if slightly) than the default parameters. In contrast, the tank-level prediction algorithm achieved the same score with the optimal combination of parameters found throughout hyper-parametrisation.

Table 8. Hyperparametrization values

GridSearchCV : parameters	
"criterion"	['squared_error', 'friedman_mse', 'absolute_error', 'poisson']
"max_depth"	[7, 10, 15,20,25]
"min_samples_leaf "	[20, 40, 100]
"max_leaf_nodes"	[5, 20, 100]
Results for Ps(t+1)	**Results for Ls(t+1)**
criterion='absolute_error', max_depth=25,min_samples_leaf=20, random_state= 42 , max_leaf_nodes=100 SCORE:99.92%	random_state=42,criterion='squared_error', max_depth= 10, max_leaf_nodes=100, min_samples_leaf=20 SCORE: 99.75%
random_state=42 (other default parameters) SCORE:99.98%	random_state=42 (other default parameters) SCORE: 99.75%

In order to demonstrate the goodness of the artificial intelligence algorithm, learning curves were also extracted (Figure 10), which highlighted several aspects:

- the convergence of the training and test curves: these curves converge, which indicates that the model is generalising well to the new, un-processed data. This is a positive sign that the model is not over-fitting the training data;
- the distance between the two curves: it is rather narrow, especially in the final stages of learning. This suggests that the model has a good generalisation capability even with a larger number of training examples;
- the model stability: beyond a certain threshold of training data (approx. 10,000 examples), the increase in the number of training examples does not seem to produce a significant improvement in the model's performance. This may indicate that the model has reached its maximum learning capacity with the current data and characteristics.
- the areas of high variance: In the initial part of the curve, there is an area of high variance as shown by the shaded areas, which represent the standard deviation of the scores. This indicates that the model is less stable and more sensitive to the particularities of the training data when the amount of data is limited.

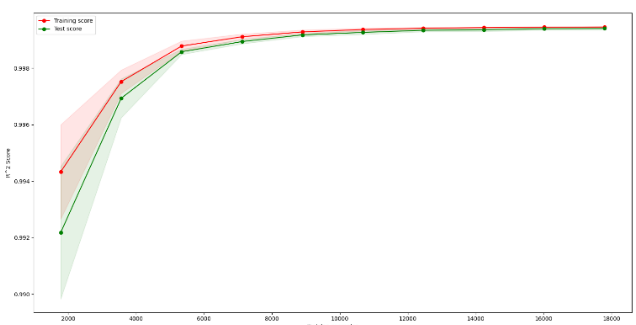

Figure 10. Learning Curves- R^2 metrics

Figure 11 and Figure 12 show the results: since the predictions of both AI algorithms are nearly 100% correct, it is not easy to distinguish between the two graphs, predicted and real data. Therefore, the correlation graph between the predicted and actual pressure and reservoir level variables is also proposed. The fact that the two graphs return with an almost perfect straight line guarantees that the prediction is accurate. To validate these two models obtained with AI, it is possible to select the collected data N°4 from Table 7, which describes the situation with the manual valve 3 at level 3 that is 100% closed (90° rotation). Level and pressure prediction results, real data and relative errors can be seen in Figure 13 and Figure 14.

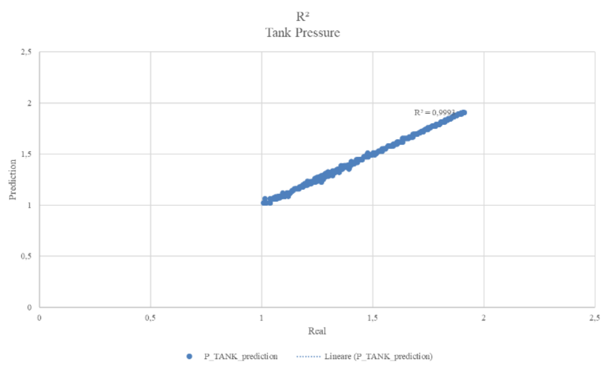

Figure 11. Tank Pressure- R2 evaluation

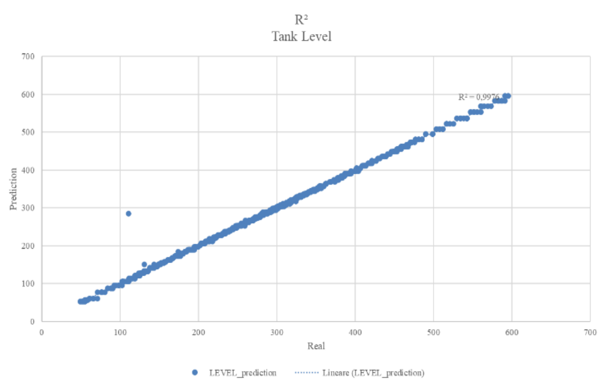

Figure 12. Tank Level - R2 evaluation

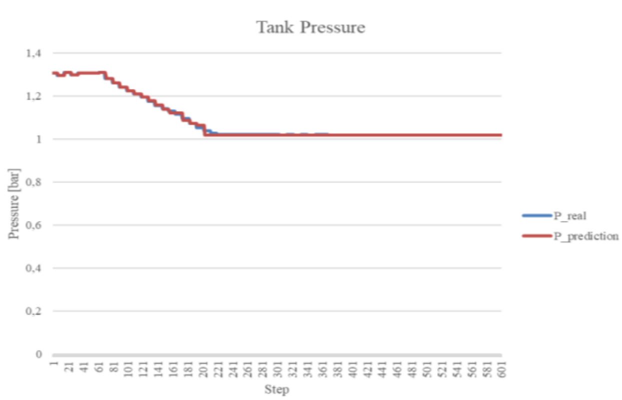

Figure 13. Tank Pressure -V3 100% closed

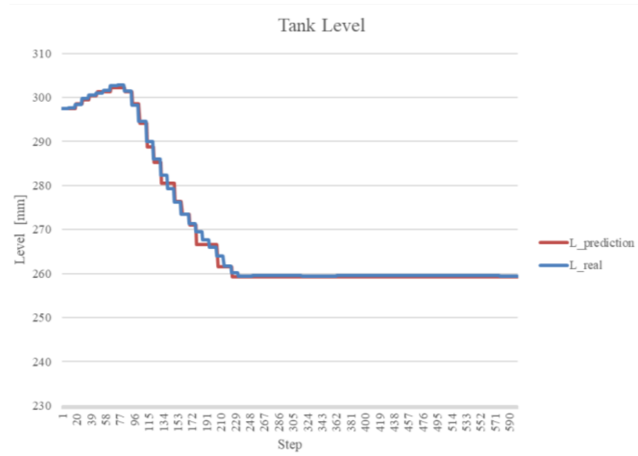

Figure 14. Tank Level-V3 100% closed

The same kind of analysis can be evaluated by considering the data of tests No. 11 and 12 in Table 7 in which air valve 7 is closed at level 1 and 2 (corresponding to about 33.3° and 66.6°). The results are displayed in Figure 15, Figure 16, Figure 17, Figure 18. The choice to specifically control these data sets (manual valve 7) is because manual valve 7 controls the air entering the system. The air in the system represents the most critical parameter in the study and modelling of the entire system. Demonstrating that the AI algorithms can correctly predict the pressure and level values of the reservoir as the inlet air changes means that the system can also capture the critical importance of this fluid and, consequently, a faithful prediction of the vertical tank system.

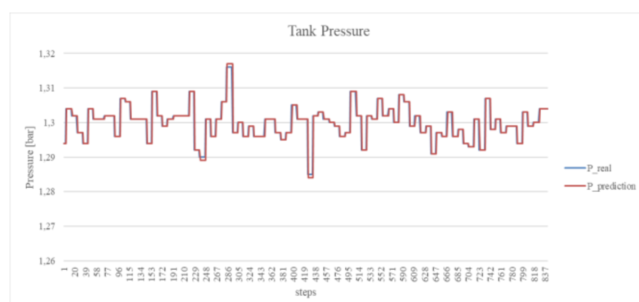

Figure 15. Tank Pressure - V7 33,3% closed

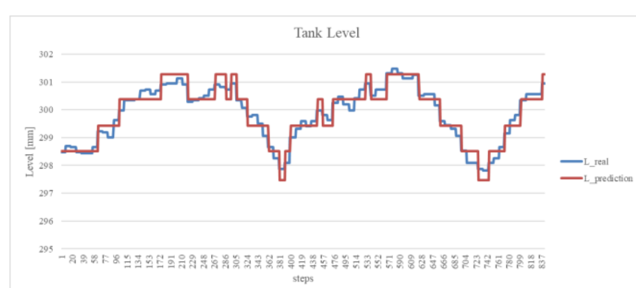

Figure 16. Tank Level - V7 33,3% closed

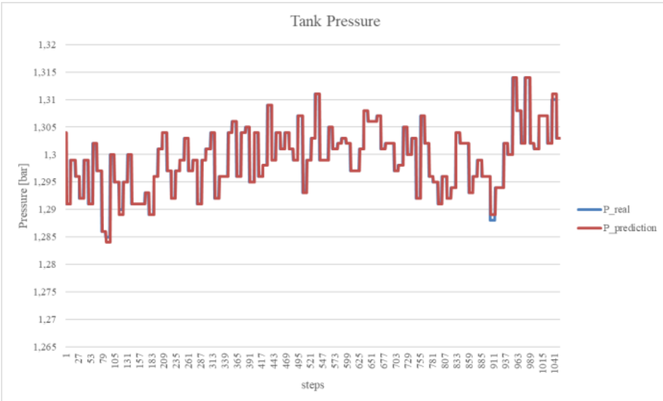

Figure 17. Tank Pressure - V7 66,6% closure

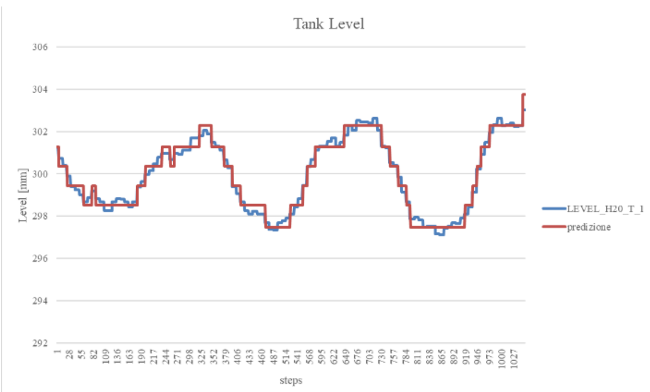

Figure 18. Tank Level - V7 66,6% closure

6. Conclusions

This paper highlights the promising integration of Artificial Intelligence and Digital Twins in the **O**il & **G**as industry, highlighting their role in real-time plant management. The proposed innovative approach uses AI models to model plant elements and integrate them into a Digital Twin, realising more dynamic and predictive management of complex plant operations. One of the main results of this research is the demonstration of the effectiveness of AI models, particularly Decision Tree Regressors, in predicting with exceptional accuracy the pressures and water levels of a vertical reservoir of an experimental plant present in the DIISM laboratories. Modelling the behaviour of this system makes it possible to anticipate and eventually manage variations in the plant's operating conditions, thus possibly simultaneously reducing the risk of failure and improving the overall safety of operations. In addition, using Digital Twins based on AI models enables real-time analysis of the conditions of the experimental plant, especially of the vertical tank-related section. Also, it enables the possibility of conducting offline/online simulations. This approach represents a significant advance over traditional non-real-time analysis methods, which may be more limited in their ability to respond quickly to changes in operating conditions. However, while this study has demonstrated the potential of combining AI and DT in the oil and gas industry, challenges remain to be addressed. For example, integrating AI and DT systems requires a robust technology infrastructure and accurate data management to ensure the quality and reliability of forecasts. In addition, there is a need to continue to develop and refine AI models to address the ever-increasing complexity of industrial plants and further improve the performance of Digital Twins. In conclusion, this study provides a solid foundation for future developments in the field of Oil & Gas, highlighting the transformative potential of the integration of Artificial Intelligence and Digital Twins to significantly improve the efficiency, safety, and sustainability of operations in the industry, thus helping to drive the industry toward a smarter and more innovative future. As future developments, the aim is to complete the model development of the entire experimental facility to build a complete Digital Twin of the entire experimental facility; in particular, it is necessary to explain why and how to connect all the models developed to each other and how to integrate better with the PID system. Once the entire experimental plant is described and represented by the DT, it could be interesting to study the possibility of identifying anomalies and distinguishing if they are generated by a malfunction or cyber-attack. The last step will be to translate the system into SimPy, an open-source library in Python designed to support the modelling and analysis of complex systems and connect the system via MQTT communication to make it externally accessible.

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