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Digital Twin of an Intelligent Completion System for Anomaly Diagnostic/Prognostic

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Intelligent completion systems (ICS) aggregate value to the oil extraction process, as they aim to increase the reservoir recovery factor. Formed by a set of valves, control and monitoring components, the system is subject to failures during adjustment manoeuvres, due to the high complexity of equipment's number and drive mechanisms, or extreme operational environmental conditions of temperature, pressure, flow and natural contaminants. For this reason, intervention actions to maintain the operational assurance of the ICSI are necessary, especially when advanced information and data about the health condition of critical components are provided through Prognostic Health Management (PHM), a maintenance approach that allows predictive analysis based on the operating conditions and health of the assets. From this perspective, the adoption of the Digital Twin (DT) technology proposed in this paper allows modelling the dynamic behaviour of the ICS in detecting interval control valve (ICV) anomalies. The approach involved the collection of operational data and parameters of the physical asset, followed by the creation of the Digital Model (MD) in dynamic/modular software for the hydraulic control of a producing well in the Brazilian pre-salt with three zones. Numerical validation, development of the diagnostic/prognostic Machine Learning algorithm and training were established in the off-Board Diagnostic (off-BD) structure, with integration into a database to capture the normal and failure states of the ICV. The implementation of the DT off-BD phase demonstrated promising results by enabling the identification of anomalies in the pressure profile correlated to the gradual opening of the ICV in three operating scenarios. In this sense, the DT will support decisions based on system behaviour to predict failures and health management of undesirable events. Furthermore, it is expected to improve the analysis of deviation diagnosis, system integrity and symptom investigation, reliability, system health management and decision making.

Keywords: Intelligent Completion, PHM, Digital Model, Digital Twin, failure diagnostic.

1. Introduction

The technologies embedded in offshore oil extraction processes have continuously evolved to meet the demand for increased fluid recovery in shorter timeframes with greater reliability. In this context, the development of intelligent wells represents a significant advancement, as it aims to enhance oil and gas field exploitation through a set of equipment and components designed to optimize production. This is achieved by integrating surface and subsurface systems and enabling remote control of downhole tools, combined with real-time monitoring for decision-making based on data analysis (Huiyun et al., 2020).

In this architecture, the objective is to extract data about flow conditions through the collection variables, transmission, and making information available to support the engineering sector in determining which adjustments should be implemented or planned (Sleptsov et al., 2024).

Thus, in Intelligent Completion (IC), integrated systems perform measurement and monitoring functions using pressure, temperature, and flow sensors for dynamic well management through the remote control of valves to meet production targets. Consequently, system reliability is essential, with electro-hydraulic systems being particularly critical to ensure operational performance and maximize hydrocarbon recovery (Carvajal et al., 2018; Taha and Amani, 2019).

However, the installation of components in this model is associated with high systemic complexity, and the challenges of reliability engineering, along with maintenance activities including workover interventions highlight the need for increased focus on developing solutions (Carvajal et al., 2019; Afuekwe and Bello, 2019).

Failures in actuation, spurious activations, and operational abnormalities are classic examples that affect effective management (Santana et al., 2020). There is a challenge in characterizing types of anomalous behaviour, as they do not always result in problems. Despite continuous monitoring, the relationship is not a direct cause-and-effect link for isolating a failure, which presents an opportunity for advancements in component health prognostics.

The use of Prognostics and Health Management (PHM) for failure detection requires instruments capable of capturing system degradation below the required performance levels (incipient or imminent failure), ensuring that changes in physical properties are identified through detectable phenomena (Vachtsevanos et al., 2006).

Thus, the research aims to employ physical models that can represent a class of real-world problems to extract information from electrical, mechanical, and hydraulic dynamic events present in engineering systems, as suggested by Sushil (2002). This approach facilitates diagnosing unforeseen anomalous phenomena and estimating the "health state" of the target component based on data.

The strategy proposed in this article involves the development of a physical asset model of the Intelligent Completion System (ICS), focused on the direct electro-hydraulic circuit used to actuate the Interval Control Valve (ICV) of the on-off type. The Digital Model (DM) designed in this phase of the research, defined as an off-board Digital Twin since it is not connected to any operational field system, incorporates embedded sensors to generate data on the valve's operational dynamics. This enables the identification of changes in actuation patterns for potential anomaly analyses. As a first exploratory analysis, the proposed Digital Twin (DT) operates as an off-board system, primarily designed for diagnostics. It enables anomaly detection and failure prediction based on historical and simulated data, supporting decision-making in system maintenance and reliability analysis.

2. Intelligent Completion System and Failures

The ICS consists of various systems and components, such as sensors and valves installed in the production string, which are essential elements of an oil well. These components operate in an integrated manner to ensure the efficient extraction of petroleum resources, with a focus on maximizing recovery. Among the key systems in a typical configuration, five subsystems stand out: flow control, well monitoring, control and supervision, chemical injection, and the accessory system, which performs support functions. Among these, flow control holds particular significance, as it fulfils the primary role of regulating the hydrocarbon influx.

2.1. *Control Systems*

Control and monitoring of operations are carried out through the Subsea Control System (SCS), which is responsible for ensuring the functionality of equipment installed on the seabed, such as the Subsea Control Module (SCM). The SCM serves as the interface between subsea equipment and the Master Control Station (MCS) located on the production platform (Wang, 2019).

The SCM collects real-time production data from reservoirs, transmitting them to the MCS while simultaneously processing received commands to actuate valves within the well and other subsea devices (Wang, 2019; Yue, 2021).

The SCM within the scope of this research is of the electro-hydraulic type, with its functionalities categorized into low-pressure (LP) and high-pressure (HP) functions for directing and controlling ICVs. Electrical signals, interpreted by the Subsea Electronic Module (SEM), actuate directional control valves (DCVs), directing hydraulic fluid to the respective valves installed in the production string, subsea valves, safety valves, or during the execution of chemical injection operation manoeuvres.

The implementation of ICVs, along with monitoring sensors integrated into oil wells, enhances the efficiency of oil recovery processes. These valves function as flow control devices to achieve optimal fluid flow balance in reservoirs containing water, gas, and oil (Bomtechia et al., 2023) or to enable injection into distinct segments or zones of wells equipped with such control systems (Al-Khelaiwi et al., 2010).

ICVs are classified into two categories based on choke configuration: on-off and multiposition (Santana et al., 2020; Bontechia, 2021). In the simpler on-off configuration, the valve is designed to operate exclusively in two states, fully open or fully closed, without the possibility of intermediate positions. In contrast, multiposition ICVs allow various intermediate flow area configurations, enabling more gradual and precise control of flow dynamics during the extraction of fluids from the reservoir to the surface (Bontechia, 2021). The flexibility offered by valve operation enhances the modular capability for precise flow rate control and can significantly optimize the efficiency of oil recovery processes (Santana et al., 2020). This approach not only maximizes production but also minimizes the influx of undesirable fluids, contributing to the effective management of the reservoir's available energy (Barreto, 2015).

2.2. *Types of Failures in ICV*

Three main "environments" can be defined around ICVs for anomaly analysis and exploration of possible effects and measurements: the annular space, the production string, and the valve control line.

The surrounding environment of the ICS is harsh as it operates under critical conditions of temperature, pressure, and fluid loads in turbulent flow, with corrosive and erosive compounds that affect the equipment's lifecycle (Rahman et al., 2012). In this context, downhole tools installed in the system, particularly the ICV in the production string, are exposed to failure risks due to their role as the interface between the reservoir and the lifting system.

These critical conditions supported by the FMEA study of ICVs published by Rahman et al. (2012), which identifies three classes of failures related to operational issues: leakage in the hydraulic chamber, flow control loss, and leakage due to metal-to-metal exposure.

The causes identified in a hierarchical tree structure include erosion, corrosion, debris, wear from excessive loading, elastomer aging, chemical attack, as well as structural degradation and mechanical damage of the valve.

3. Adopted Methodology

3.1. *General Structure*

This study focuses on the direct hydraulic (DH) system of the ICS operating in ultra-deepwater, divided into the following stages (Figure 1):
(i) Collect data and analysis of normal ICS operations and failures and (ii) Select information on systems and operational components related to

actuation functions for the activation and deactivation of the ICV. The next stage is (iii) Develop the DM, analysis the dynamics and mechanisms of the ICV, and validate the model. The final stage involves (iv) Generation of data and scenarios using the DM. (v) Build a Machine Learning (ML) off-board diagnostic algorithm for the Digital Twin framework; (vi) Generation of new data for scenario evaluation; and (vii) Analysis of results and characterization of anomalies.

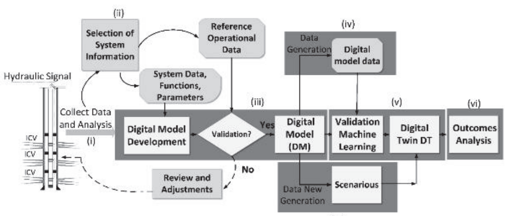

Fig. 1. Development Stages Diagram.

3.2. *Physical asset architecture and data*

The physical asset architecture comprises the DH system structured by the hydraulic power unit (HPU), the SCM, and the wellbore (Figure 2). The systems engineering approach defined by their components:

(i) Hydraulic Power Generation (topside): Includes flow sensors, pump, accumulators, relief valve, and transducers.

(ii) Subsea Control Module (SCM): Where the directional control valves (DCVs) are located.

(iii) Wellbore: Contains two ICVs, represented by two pistons with open/close function lines.

A group of six pressure transducers and two flow meters provides direct monitoring data for the power fluid within the circuit.

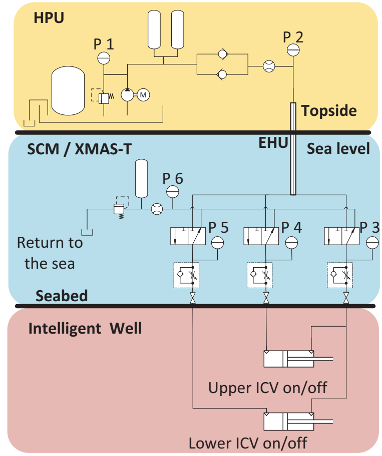

Fig. 2. Simplified Structure of the Hydraulic Flow Control System

The modelling focuses on the execution of the opening and closing function of the on-off type ICV as the initial exploratory approach for research and development. The primary dimensional and operational data for the ICV presented in Table 1.

Table 1. Dimensions and Operating Parameters of the ICV.

Parameter (unit)	Value
Size (in)	4 ½
Maximum Working Pressure (psi)	10,000
Differential Unloading Pressure (psi)	5,000
Maximum Hydraulic Chamber (psi)	10,000
Minimum Internal Flow Area (in.^{2})	11.04
Piston Area (in.^{2})	3.28
Total Stroke (in.)	6.00
Hydraulic Chamber Volume (in.^{3})	9.11

3.3. System Modeling

The DM was developed on the MATLAB® platform, version 2021, using a block-based functional structure through the Simulink and Simscape packages. These packages integrate a set of differential equations in the domains of translational mechanics, hydraulics, and fluid dynamics. The blocks represent components within the system—hydraulic pump, accumulator, relief valve, flow lines, and pistons—to model the behavior of the power fluid flow in each phase of the system: HPU, SCM, and wellbore.

The objective is to simulate the actuation of the hydraulic piston responsible for moving the valve spool between the on and off positions and to extract data on flow and pressure load in the system regions, focusing on sensitive points that may indicate anomalies or virtual failures.

The performance measurement and validation of the model follow the methodology proposed by Sargent (2020). The modelling results compared with the system's reference operational data are compared and evaluated to verify the consistency of the system's physical responses, aiming to estimate accuracy.

3.4. Machine Learning (ML)

The Machine Learning workflow stage is structured using data generated by the DM, extracted from sensors at specific points representing its simulated physical twin for the variables of pressure load and flow. The information exported from MATLAB for each sequence of ICV actuation commands constitutes the dataset of operational conditions used in the training and validation process of the model.

In this modelling process, the preparation phase involves selecting the batch of generated data, followed by its division into two main groups: training data, corresponding to 80% of the total, and test data, accounting for 20%. This division aims to mitigate inadequate prediction results and avoid overfitting. The division was organized to ensure a balanced representation of the system's dynamic characteristics by arranging the dataset based on profiles of interest related to pressure and flow curves. All procedures were conducted in Python 3.7 for ML production supported by the Scikit-Learn and Imbalanced-learn libraries, which are used to balance failure classes.

The preprocessing phase included normalization and standardization of variables, as well as the identification and treatment of outliers based on the system's intrinsic behavior to ensure data consistency. The ML algorithm used in this exploratory study was Random Forest, chosen for its superior interpretability and suitability for smaller data volumes. Additionally, as highlighted by Aslam et al. (2001), its robustness and accuracy stem from its ability to combine multiple decision tree models, making it effective even with limited datasets. The metrics used to evaluate the model's performance were Accuracy, F1-Score, and Area Under the ROC Curve (AUC).

3.5. Failure Scenarios

The failure scenarios were derived from three sources: literature review, failure databases from Wellsom ICVs recorded by three manufacturers, and results from a Failure Modes, Mechanisms, and Effects Analysis (FMMEA) conducted by experts for the ICS, guided by ISO-14224 standards.

In this context, the FMMEA results identified mechanical, hydraulic, and electrical failure modes that can be modeled in the DM by altering physical parameters to represent a level of anomaly. The FMMEA structure for the ICS was developed for the subsystem of interest to indicate various failure trains. As an example, the architecture demonstrates two failure modes used in the research: hydraulic failure and structural mechanical failure (Figure 3).

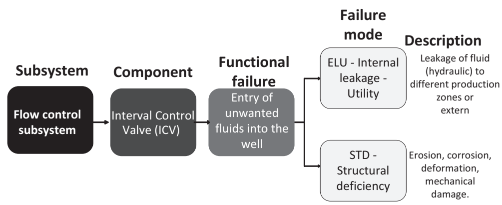

Fig. 3. Example of the failure mode extracted from the FMMEA for scenario simulation.

4. Results

The proposed model demonstrated, through pressure curve profiles in the hydraulic system, a similarity to the physical asset. Preliminary responses reveal operational loads in the range of 500 to 600 kgf/cm² at the SCM, with a dynamic behaviour pattern closely aligned with the ICS's operating range in the return line. In Figures 4 and 5, the valve activation illustrates piston movement associated with pressure variation in the system, with a compatible hydraulic volume consumption.

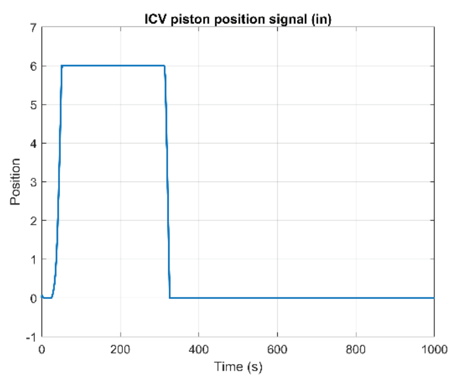

Fig. 4. Piston displacement of the ICV.

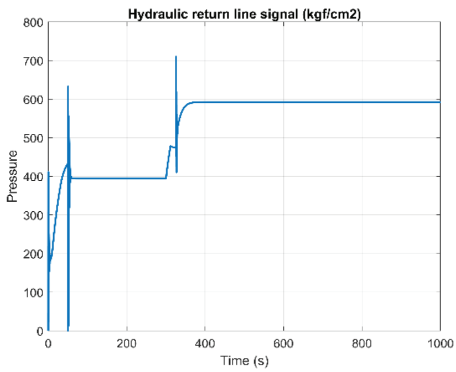

Fig. 5. Pressure in the return line.

The hydraulic volume consumed during activation is depicted in Figure 6, showing an operational range consistent with the expected performance of the system.

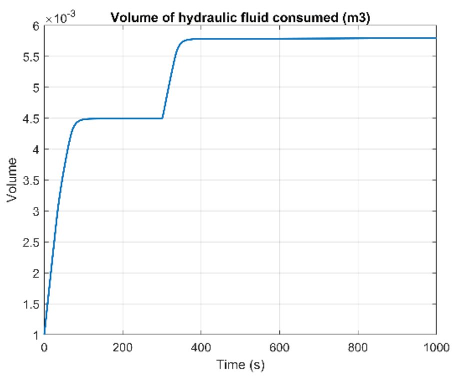

Fig. 6. Hydraulic fluid supply volume

The results conceptually validate the model for quantitative assessment when compared to the volume and pressure profiles of the physical asset in the well. The metrics Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) indicated moderate accuracy (values between 100 and 150) for hydraulic fluid consumption volume and high accuracy (below 100) for pressure variation (Table 2). Consequently, the model can be considered partially adequate, as the two variables of interest exhibit differing accuracy levels and remain relatively distant from zero, the ideal value representing robustness.

Table 2. Model performance evaluation metric.

Metric	**MAE**	**RMSE**
Hydraulic fluid volume	125.5	205.8
Return pressure	85.0	98.5

Despite its non-ideal performance, the modeling data for operational and anomalous functions were generated to support the ML process. Data production conducted over a simulation interval of 0 to 1000 seconds, with exported information, were categorized into two health states: normal and failures. These states were labeled as follows: 0 - Normal behavior; 1 - Hydraulic failure, attributed to loss of containment in the hydraulic system caused by punctures or cracks in lines and devices; and 2 - Mechanical damage to the piston due to structural alteration, represented by a change in the damping coefficient parameter of the ICV component (Table 3).

Table 3: Failure classes and fault labels.

Failure mode	**Components**	**Label**
None	all	0
Hydraulic	Hydraulic line	1
Structural	Piston (ICV)	2

The failure profile curves were generated by altering the model's parameters and adjusting the block configuration to ensure the convergence of the model's system of equations.

As shown in Figure 7, through the confusion matrix, it is possible to evaluate the model's performance in classifying the test data. The model demonstrated robustness in identifying class 0, correctly classifying 20 instances. However, three instances were erroneously classified as belonging to class 1 and two were assigned to class 2 when they should have been classified as normal behavior. These errors, in a real-world scenario, are considered false positives, as they could trigger false alarms and consequently lead to unnecessary actions.

For class 1 all model predictions were correct, demonstrating high precision in this category. Class 2 had four correct classifications. However, two instances that also presented mechanical damage were classified as normal behavior. In a real-world scenario, these classifications would be considered false negatives. This type of error is more critical since, in practice, it could prevent the technical team from being alerted to the occurrence of mechanical damage, increasing the risk of more severe damage and higher operational costs.

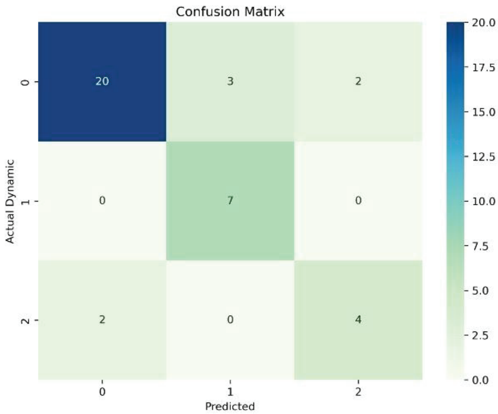

Fig. 7. Model confusion matrix

The results, shown in Figure 8, demonstrate the model's ability to generalize anomaly identification, achieving 82% accuracy in response performance, with an F1-score of 78%, as well as 78% Macro AVG and 82% Weighted AVG. Additionally, the model exhibited 70% sensitivity, 100% recall, and 82% F1-score in identifying Type 1 failures (Hydraulic) and 67% sensitivity, 67% recall, and 67% F1-score for Type 2 failures (Structural).

For identifying curves classified as normal, the model achieved 91% sensitivity, 80% recall, and 85% F1-score, supporting the quality of the proposed model. However, the developed modelling still presents some weaknesses, such as: the limited amount of data for exploring various failure types proposed in the FMMEA method, the need to improve model accuracy by expanding quantitative metrics and potential to enhance the model by incorporating scenario databases with extended time-series.

Classification Report:

	precision	recall	f1-score	support
0	0.91	0.80	0.85	25
1	0.70	1.00	0.82	7
2	0.67	0.67	0.67	6
accuracy			0.82	38
macro avg	0.76	0.82	0.78	38
weighted avg	0.83	0.82	0.82	38

Fig. 8. Outcomes of Machine Learning Modeling

5. Conclusions

The research proposed the construction of a DT for anomaly analysis and failure estimation through data generation by the DM and ML analysis.

Developing studies to identify anomalies in complex systems, driven by the laws of physics and data analysis, combining digital modelling and machine learning, is an approach that offers significant advantages for data-based diagnostics.

Although different failure scenarios can be simulated through the DM to generate a more comprehensive dataset and feed the ML model, one of the main challenges is integrating these models into a single system. This integration requires the creation of a continuous feedback loop, where insights generated by ML are used to refine and recalibrate the DM.

For future propositions, it is recommended to test other ML models to assess which best suits the dataset. Finally, applying the Digital Twin to a producing well in the pre-salt layer is suggested to validate the efficiency of the proposed framework.

The proposed approach is particularly relevant in ICS, which presents various alternatives for failure causes and effects, impacting production planning. The framework serves as a foundation for future developments and a guide for new research directions aimed at improving the reliability of failure diagnostics in oil wells operating with intelligent completion technology.

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