DIGITAL REDUNDANCE FOR COMPACT SUBSEA ELECTRO-HYDROSTATIC ACTUATORS USING SENSOR FUSION

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ABSTRACT

Compact electro-hydrostatic actuators (EHAs) offer a promising solution for subsea production with their cost-effective and energy-efficient design, combining the benefits of electromechanical and electro-hydraulic systems. However, adapting these compact EHAs to fit within the limited space of traditional subsea systems poses a challenge, particularly in maintaining system reliability. This study introduces a Digital Twin (DT), composed of a physical EHA model and multiple Kalman Filters for parameter estimation, aimed at creating digital redundancies for critical sensors. The effectiveness of this approach was validated using co-simulation with Dymola software, where a simulation model emulated both the Plant (Real Twin), as a Modelica model, And a mathematical model as a software object (Digital Twin). The results demonstrate reliable digital redundancies for position and load measurements, with minor deviations that are within acceptable limits.

Keywords: Compact Electric-Hydrostatic Actuator, Fault tolerance, Digital Twin, Subsea Valve Actuator.

1 INTRODUCTION

The transition from conventional hydraulic and electro-hydraulic to electro-mechanical apparatus in subsea oil & gas exploitation fields is a growing trend, referred to as the "All-Electric Subsea" approach. This shift offers multiple advantages including reduced installation (CAPEX) and operation costs (OPEX), quicker system response, increased energy efficiency, reduced umbilical cable diameter (due to the elimination of hydraulic lines), enhanced operational flexibility, and environmentally sustainable design [1][2]. Electro-hydrostatic actuators (EHAs) are integral to this approach, amalgamating the benefits listed above with those of traditional electro-hydraulic systems, such as compactness, robustness, high power density, high load capacity, and effective overload protection with fail-safe functions performed by springs [3][4].

A significant challenge in implementing EHAs – self-contained control systems with numerous components – is the requirement to accommodate these within the space that is traditionally occupied by subsea hydraulic actuators. Figure 1 illustrates the various modules comprising a rotary electro-hydrostatic subsea valve actuator, designed to fit within the dimensions of a conventional hydraulic cylinder [4].

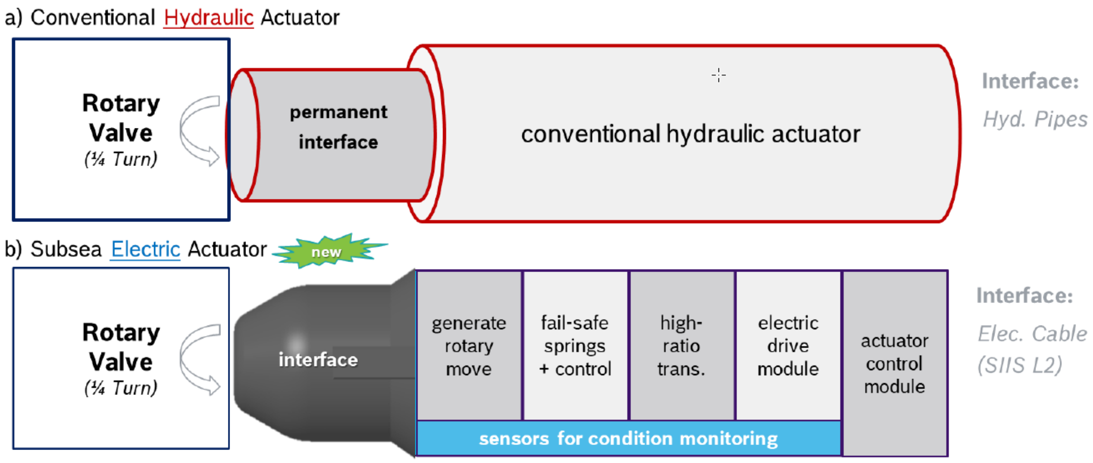

Figure 1 - Comparison of components integrated in a new Subsea rotary EHA [7].

The limited space in these intricate systems restricts the inclusion of redundant components, calling for alternative approaches to improve system reliability. Orth *et al*. [7] and Placido Neto *et al.* [8] highlight a significant challenge in applying EHA technology to replace hydraulic Subsea Valve Actuators (SVAs) where the new designs must fit into the space occupied by conventional units. This spatial limitation can restrict system redundancies, necessitating alternative approaches to bolster reliability.

To tackle this issue, a Digital Twin (DT) – a high-fidelity simulation model integrated into the actuator's controller [6] – presents itself as an effective solution. Capable of accurately reflecting the actual system's behavior, it acts as a digital backup for essential sensors. To achieve this, the DT must continuously update its parameters using sensor signals and control actions from the system, stepping in to substitute the feedback from a faulty sensor in case of failure.

2 SUBSEA VALVE ACTUATOR

The focal physical system modeled in this study is an electro-hydrostatic Subsea Valve Actuator (SVA) depicted in Figure 1. The SVA is engineered for the operation of rotary small-bore valves at water depths reaching up to 4,000 meters, designed concisely to match the size and weight of traditional subsea hydraulic actuators [7]. It not only accommodates a standard electric interface but also seamlessly integrates essential components, including electric drives and controls. Moreover, the actuator is equipped with an embedded system to facilitate motion control and offers a communication interface compliant with the Subsea Instrumentation Interface Standardization (SIIS) - specifically, a fault-tolerant CANOpen (SIIS Level 2) - ensuring reliable communication for operators.

According to Kritzinger *et al.*[6], a Digital Twin must ensure that any alteration in the physical object's state is mirrored in the digital object's state. This necessitates the establishment of a well-defined set of system elements that constitute the Digital Twin, thereby creating a control volume. This control volume defines the scope of the system covered by the Digital Twin, essentially forming a control system. A critical aspect of this process is the mapping of the system's inputs and outputs, which forms the basis for continually updating the information within the Digital Twin.

The Subsea Valve Actuator (SVA) illustrated in Figure 1 and detailed in Figure 2 is designed to operate rotary small-bore valves at depths of up to 4,000 meters [7]. The application software, housing the Digital Twin, is tailored to meet various normative, proprietary, and customer requirements, enabling the actuator to perform multiple functions. These functions, partially outlined in Placido Neto *et al.* [8], include (1) Preload fail-safe mechanism, (2) Command open of the process valve, (3) Command close of the process valve, (4) Emergency shutdown of the process valve (Fail-safe closing), and (5) Hold position.

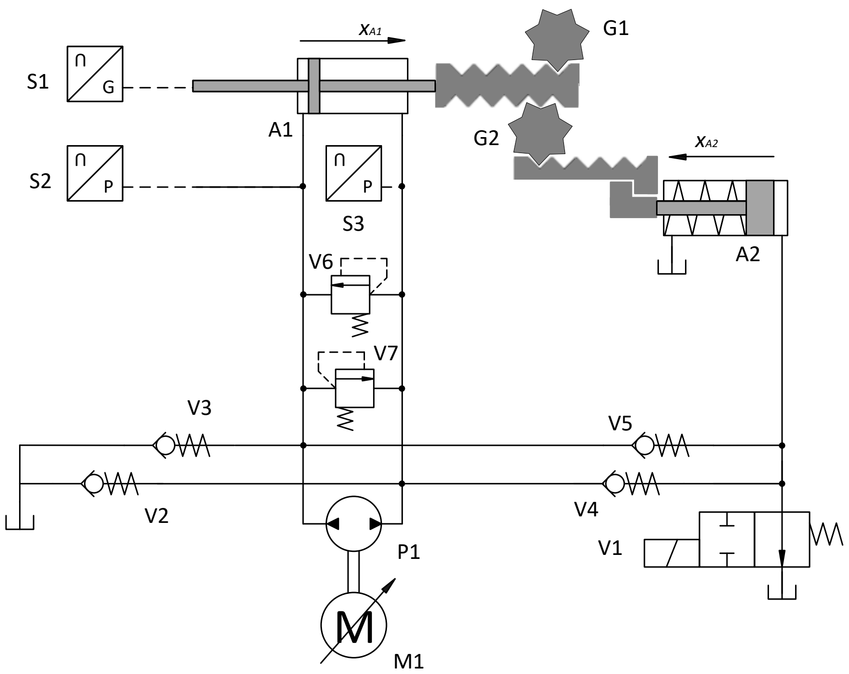

Figure 2 - Exemplary hydraulic circuit diagram

In the operation of the SVA R2, its Digital Twin must accurately replicate the behavior of its physical components. This requires the development of a robust mathematical model capable of adapting to the unique characteristics of the physical system, including manufacturing variances, environmental uncertainties, and component degradation. The details of this mathematical model and the methods for its continual updating are discussed in the following sections.

3 DIGITAL TWINS

Introduced in 2003 at the University of Michigan's Executive Course on Product Lifecycle Management (PLM) [5], the concept of a Digital Twin (DT) has evolved, yielding various definitions encompassing diverse systems and applications [9][10]. Rosen *et al*.[11] describe a DT as a highly realistic model reflecting the real-time state and behavior of a system or process interacting with the real world. According to Grieves (2014), a DT comprises three elements: physical products in real space, virtual products in virtual space, and the data connections binding the two.

Borangiu *et al*. [14] enumerate the primary benefits of DTs, including visibility (enabling operation visualization of individual equipment to larger systems), prediction (facilitating future state forecasting through modeling techniques applied to DT models), interaction (allowing condition simulation for "what if" scenario analyses impractical with physical prototypes), documentation (providing insight into the behavior of components), and integration (implementing DT models for connection with backend business applications in large systems).

However, the proliferation of definitions, along with related concepts like digital simulation, Cyber-Physical Systems (CPSs), and the Internet of Things (IoT), often results in confusion [12]. Some works between 2016 and 2019 referred to models as DTs even though they lacked essential DT attributes [13]. To clarify, Kritzinger *et al.* [6] propose classifying DTs into three subcategories: Digital Models, Digital Shadows, and Digital Twins, each representing different degrees of data integration and interaction between the physical and digital entities:

- Digital model: a digital representation of an existing or intended physical object that does not use any form of automatic data exchange between physical and digital objects. The communication between both objects is done manually. The digital representation may be more or less accurate in relation to the physical object;
- Digital shadow: In the digital shadow, there is already an automatic one-way flow of data between the state of the existing physical object and the digital one. A change in the state of the physical object leads to a change of state in the digital object, but not in a opposite way;
- Digital twin: data flow between the existing physical object and the digital object is fully integrated into both directions. The digital object can also act as a control instance for the physical object.

Kritzinger *et al*. [6] underscore that a Digital Twin must reflect changes in the physical object state with corresponding changes in its digital counterpart. Consequently, it is imperative to delineate a precise set of system elements comprising the Digital Twin. This process effectively constructs a control volume, delineating the scope of the system encompassed by the Digital Twin and forming a control system framework. Essential to this endeavor is the accurate mapping of the system's inputs and outputs, serving as the foundation for information updates within the Digital Twin.

4 SENSOR FUSION

According to Liu and Ma [15], sensor fusion is about combining information from different sensors to get a complete picture of an area or object. For example, in autonomous vehicles (AVs), various sensors are placed in different spots to help the vehicle understand its surroundings from all angles. Sensor fusion becomes really important when there is a lot of information coming from different directions. It helps identify the same object seen by different sensors and puts together all the information from these sensors to create a big, unified picture of the area being sensed.

In the Industrial Internet of Things (IIoT) context, sensor fusion is an approach also applied to predict faults in industrial equipment where the data from multiple sensors is combined in order to aid the continuous operation without interruptions [16]. The sensor fusion approach is also applied in hydraulic power systems in the detection of faults, as presented by Zhong *et al.* [17], Chen *et al.* [18], and Shi *et al.* [19]. Kalman filter algorithms are also strongly used in sensor fusion approaches as shown in Kheirandish *et al.* [20] and Demirci *et al.* [21].

For hydraulic systems of medium and/or high complexity, the application of a sensor fusion technique becomes more challenging, since the correlation between sensor signals can or not happen depending on the states of individual components. For example, the current in a HPU electrical motor is proportional to the system pressure just while the motor is activated. Therefore, the causality between components, depending on the system's state must be known, for a proper sensor fusion algorithm to be implemented.

In addition, to create digital redundancies for critical sensors, which is to replace the feedback signal of the fault sensor with an estimated value based on a model behavior and other sensors, it is imperative that the Kalman filter algorithm is applied to update parameters of the system, so the model can be able to work similarly to the real system even when a parameter is not updated anymore. Therefore, a finite state model of the SVA R2, as shown in Figure 3 was developed. For each state the correlation between signals is obtained through a causality analysis. Fundamentals about finite state modeling can be seen in Dathan and Ramnath [22].

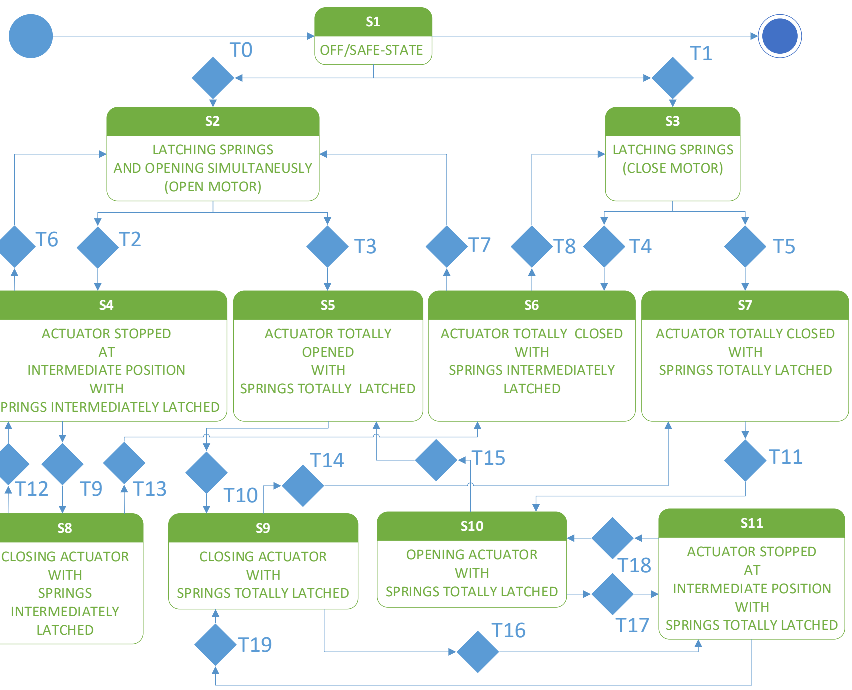

Figure 3 - State transition diagram for the SVA R2

In Figure 3 , S1 to S11 are the possible defined states of the actuator and T0 to T19 are the transitions between these states. Then, by knowing the states of the actuator, the parameter estimation algorithm uses the causality between elements to update the Digital Twin parameters.

5 DIGITAL TWIN MODELLING

There are several ways of building the structure of dynamic systems models, such as Physical Models, where is system is divided into subsystems whose behaviors are known, Identification Models, where observations from the real system are used to fit in a chosen model structure, or even neural networks [23] [24] [25] [26]. Dynamic models are also divided into deterministic and stochastic models, being deterministic if they present an exact relationship between measurable and derived variables and work without uncertainty or stochastic if they present uncertainty or probability concepts [24].

The objective of this work was to develop a physics-based Digital Twin, with a parameter estimation system to update the DT main parameters based on sensors' readings and control actions. Hence, state-space modeling, or dynamic linear modeling, presented itself as a fit solution for its development, once it is a general modeling structure that allows the combination of deterministic equations with uncertainty components [27].

As given by Shumway & Stoffer [27], the basic form of the state-space model employs an order one, n-dimensional vector autoregression as in

$$x_k = \Phi_k x_{k-1} + w_k \tag{1}$$

$$y_k = H_k x_{k-1} + v_k \tag{2}$$

where y_k is a vector of observable variables $n\ x\ 1$, x_k is a vector of unobservable variables *m x 1* called state variables, H_k is a matrix of known coefficients and v_t is a white noise *n x 1* vector, called measurement error, with covariance $\mathrm{E}(e_k e_k') = R$, Φ_k is an $m\,x\,m$ matrix of autoregressive coefficients and w_t is a white noise *m x 1* vector with covariance $\mathrm{E}(\varepsilon_k {\varepsilon_k}') = Q$, called state error.

Inputs variables may enter into the states or into the observations, where a *r x 1* inputs vector is added to equations 1 and 2, as

$$x_k = \Phi_k x_{k-1} + \Upsilon u_k + w_k \tag{3}$$

$$y_k = H_k x_{k-1} + \Gamma u_k + v_k \tag{4}$$

where Υ is a $n\ x\ r$ input matrix and Γ is a $q\ x\ r$ feedforward matrix.

In order to obtain a modular design of the Digital Twin program (see Dathan *et al.* [22]), composed of individual modules, which are the mathematical models of individual components or component assemblies of the system, a modular state-space modeling based as described by Wang *et al.* (2018) and Yang and Wang [28] is chosen to be implemented.

6 PARAMETERS ESTIMATION USING KALMAN FILTER

The Kalman filter has been applied in several areas to describe the evolution of dynamic systems, where its main objective is to update the knowledge of a system each time a new observation is brought in [30] [31]. The algorithm objective is to find estimates of unobservable variables based on related observable variables through a set of equations called a state space model, which were already depicted in Equations 1 and 2.

In this work, the Kalman filter was implemented to estimate the parameters of the Digital Twin, instead of states. As shown in Liu [32] and Grewal and Andrews [33], the Kalman filter can be implemented to simultaneously estimate states and parameters by the addition of the observed parameters in the state vector. As an example, assuming two parameters a and b, included in the equation and as follows

$$x_{k+1} = f(x_k, u_k, a_k) + w_k \tag{5}$$

$$y_k = g(x_k, b_k) + v_k \tag{6}$$

$$a_k = a_{k-1} \tag{7}$$

$$b_k = b_{k-1} \tag{8}$$

The implemented algorithm was written as described in Costa & Alpuim [30]. Below, the iterative algorithm for updating the DT pump volumetric efficiency is depicted. During states 9 and 10, see Figure 3, the algorithm produces an estimator of the parameter η_{v_k} at each time k, based on the information up to time $k-1$, as given by

$$\hat{\eta}_{v_{k|k-1}} = \hat{\eta}_{v_{k-1|k-1}} \tag{9}$$

when at time k, η_{v_k} is available, the prediction error or innovation v_k is given by

$$v_k = \eta_{v_k} - \hat{\eta}_{v_{k|k-1}} \tag{10}$$

η_{v_k}, in steady-state, is calculated through

$$\eta_{v_k} = \frac{A_{A1}\dfrac{dx_{A1}}{dt}}{D_{P1}\omega_{P1}} \tag{11}$$

where A_{A1}[m^2] and x_{A1}[m] are respectively the cylinder A1 area and position and D_{P1}[m^3/rad] and ω_{P1}[rad/s] the pump P1 volumetric displacement and angular velocity. The error v_k is used then to estimate $\hat{\eta}_{v_k}$ with the equation

$$\hat{\eta}_{v_{k|k}} = \hat{\eta}_{v_{k|k-1}} + K_k v_k \tag{12}$$

where K_k is called the Kalman gain and is given by

$$K_k = P_{k|k-1}\left(P_{k|k-1} + R\right)^{-1} \tag{13}$$

where R is the measurement error covariance. Additionally, the mean squared error MSE matrix of the updated estimator $\hat{x}_{k|k}$ represented by $P_{k|k}$ verifies is updated by

$$P_{k|k} = P_{k|k-1} + Q - K_k P_{k|k-1} \tag{14}$$

where Q is the so called state error covariance.

7 COO-SIMULATION SETUP

The Digital Twin model and parameter estimation algorithms were developed in C code using the aforementioned equations. The C program was then compiled as an external object using the software Dymola. In the Dymola program, an already developed model simulates the Real Twin where both the DT and Modelica model received the same inputs coming from the Controller. Figure 4 shows shows the Dymola model that interconnects the three different programs.

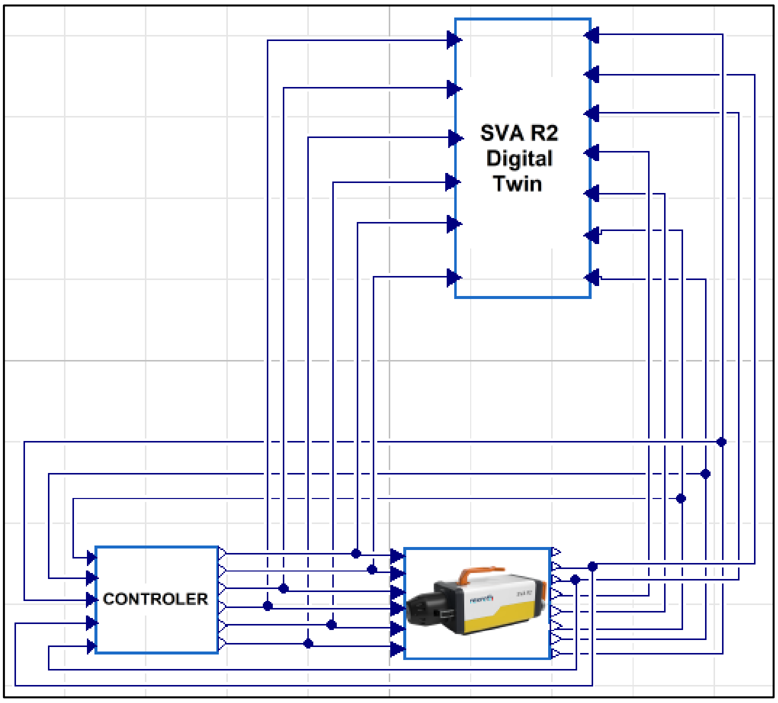

Figure 4 - Coo-simulation setup

8 RESULTS

With the coo-simulation setup developed, two different scenarios were simulated with the objective of observing the capacity of the Digital Twin parameter estimation program to adapt chosen parameters, e.g. volumetric efficiency and coulomb force, to the Real Twin and serve as a digital redundance.

8.1 Scenario 1: Regular actuation cycle with constant resistive load – No fault sensor

In the initial scenario, the effectiveness of the Digital Twin's parameter estimation algorithm is evaluated. For this test, the hydraulic pump P1 (Plant) in the Dymola model is set with a volumetric efficiency of 87.7%, whereas the initial parameters of the Digital Twin are configured at 72%. Figure 5(a) displays the position sensor signal of the SVA (Plant) [°], the digital twin position [°], the SVA (Plant) position [°], and the difference between the Plant and Digital Twin positions [°], and Figure 5(b) presents the plant and tDT pump model volumetric efficiencies. The real value of the Plant position and its sensor are shown because in scenario 2 a fault in the position sensor will be simulated and the difference between the DT position and Plant position will be of interest.

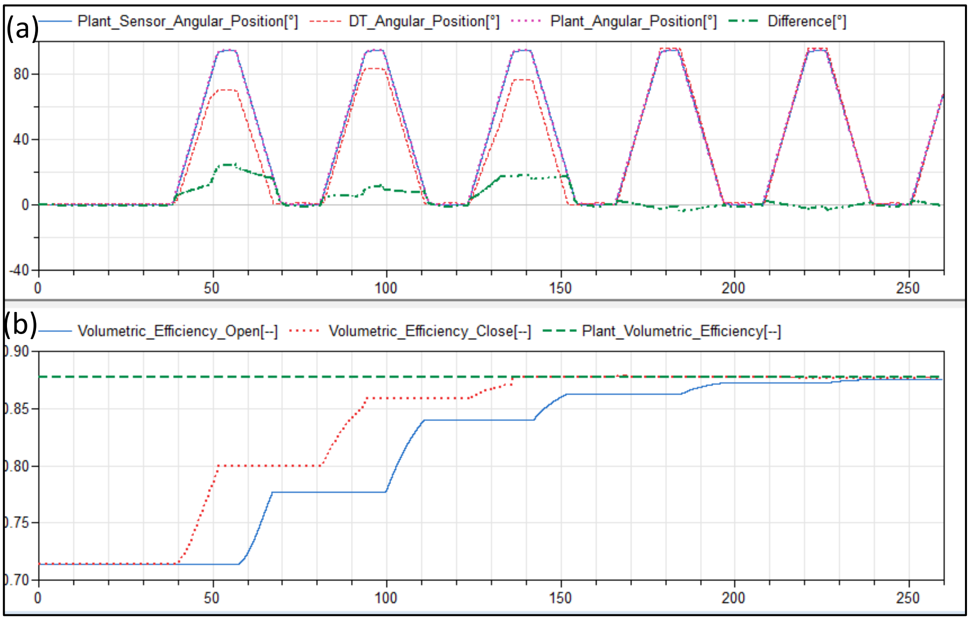

Figure 5 - *Scenario 1: Plant and Digital Twin positions as the Kalman filter parameter estimation algorithm updates the volumetric efficiency.*

It can be observed from Figure 5 (a) and (b) that the values of the open and closed volumetric efficiencies take 4 cycles to converge. At 250 seconds the difference on angular position between the plant and Digital Twin is 0.2% for open function and 0.04% for closing. Another aspect to be observed is the difference between Plant and Digital Twin positions, that has a maximum value of 24.8° for the 1st cycle and 3.36° for the 4th cycle.

It can also be observed that the parameters are just updated during the expected operational state, that means, the open and close volumetric efficiencies are updated, respectively, during the open and close operations, which are the states 10 and 9 in Figure 3. Another important variable to be monitored in a subsea valve actuator is the load torque required to operate the production valve. In this first scenario, a constant resistive load torque was applied. Figure 6 shows the plant and digital twin.

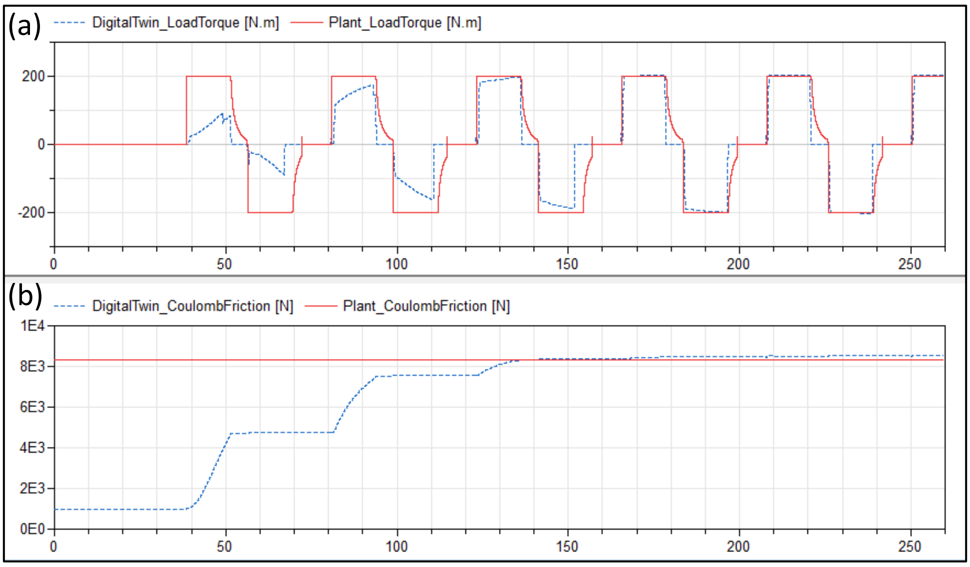

Figure 6 - Scenario 1: Plant and Digital Twin Load Torques.

The updated parameter presented in Figure 6 is the coulomb friction from the SVA load, which also updates as the cycles go forward, resulting in a torque difference of 3.5 Nm between Plant and Digital Twin model in the 4th cycle.

8.2 Scenario 2: Regular actuation cycle with constant resistive load – Fault sensor at 200 seconds

In scenario 2, a fault in the position sensor is simulated. In 200 seconds, the value of the position sensor is nullified. A *Stuck-at* detection algorithm (see Liu *et al.* [34]) is implemented to detect the faulty sensor.

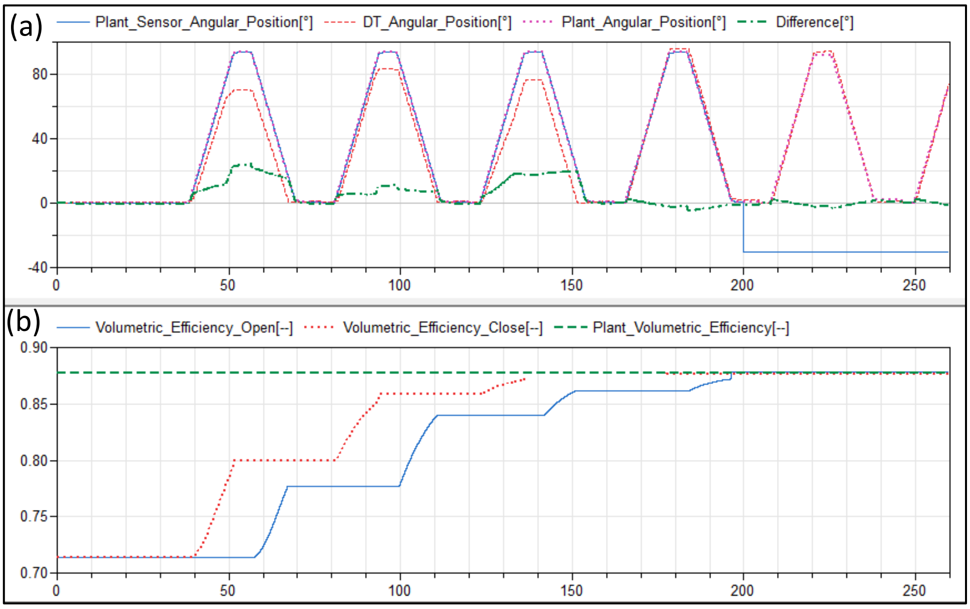

Figure 7 - Scenario 2: Plant and Digital Twin positions as the Kalman filter parameter estimation

algorithm updates the volumetric efficiency.

In Figure 7 it can be noticed that after 200 seconds, the value of the angular position sensor goes to -30°, which simulates that the sensor voltage output is zero. In this point the volumetric efficiency and load torque parameter estimation algorithm stop working and the Digital Twin position signal starts being used as feedback signal for the system controller. It can be observed by the comparison between the Plant angular position value and the Digital Twin Angular position, as well as the difference value, that the Controller is still able to control the plant while using the Digital Twin feedback signal.

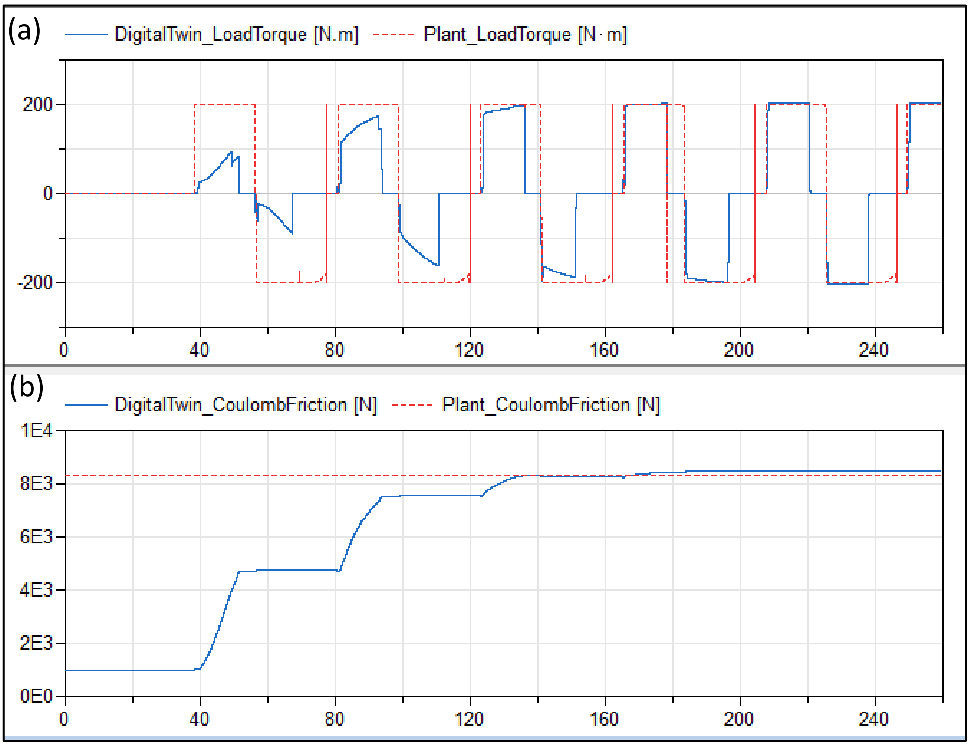

Figure 8 - Scenario 2: Plant and Digital Twin Load Torques.

Figure 8 demonstrates that the Digital Twin continues presenting a fit value regarding the real system, even after the parameter estimation algorithm is deactivated at 200 seconds.

9 FINAL REMARKS

The outcomes from the simulated scenarios show that the developed Digital Twin can successfully mimic its real-world counterpart's behavior offering a reliable level of confidence, given the required time for it to adapt its parameters as a function of the real system sensors readings and control actions. This enables tracking unmonitored variables and more importantly in the studied system, replacing malfunctioning sensors, e.g. position sensor, with digital versions that are less precise, but yet allow the system to continue its key functions with only minor dips in accuracy.

Additionally, this method can be applied to all actuated valves in a Christmas Tree subsea setup, significantly aiding in developing a comprehensive Christmas Tree Digital Twin for various subsea applications. Such widespread use enhances the detailed monitoring of equipment parameters, improving the overall condition assessment of the Christmas Tree subsea systems. The ability to enhance a fault tolerant automation system through software, without adding to its hardware complexity or incorporating extra physical components, is extremely beneficial for oil and gas subsea production or processing systems. It's also vital for cutting costs and boosting reliability and safety in emerging energy sectors like Carbon Capture Utilization and Storage systems, or offshore green hydrogen (H2) production.

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