TOWARDS HYBRID DIGITAL TWIN FOR PERFORMANCE-BASED CONTROL EVALUATION IN HYDROGEN FACILITIES

José L. Hernández[1], Ismael Lozano[1], Víctor I. Serna[1], Luis V. Jimeno[1], Jesús Samaniego[1] and Francisco J. Miguel[1]
[1] CARTIF technology center, Boecillo, Spain

Abstract

Current digital twins for hydrogen energy systems mainly rely on physics-based simulations. Still, data-driven approaches are not fully deployed, limiting the ability to support systematic evaluation of control strategies under diverse operating scenarios. This paper addresses this gap by proposing a hybrid digital twin framework for hydrogen-based testing and experimentation facilities, integrating physics-based and data-driven models, which combines time-series and contextual data. The framework enables scenario-based experimentation and performance-oriented control evaluation. While no experimental results are yet presented, the proposed approach establishes a scalable foundation for performance-based feedback loops, supporting future development of adaptive, energy-efficient, and low-carbon control strategies.

Introduction

Hydrogen energy systems are increasingly recognized as a cornerstone technology for decarbonizing energy systems and enabling high penetration of renewable energy sources. The major potential of hydrogen (H_2) lies in its versatility in production, storage, and utilization, as well as its ability to mitigate grid imbalance through long-term energy storage (Taghavi, 2026). As a versatile energy carrier, hydrogen can support sector coupling between electricity, heating, and mobility, while providing long-term storage and flexibility to energy systems with high shares of variable renewable generation.

Recent research highlights the expanding role of hydrogen in integrated energy systems. The objective is to enhance system flexibility across electricity, heat and transport sectors (Bhandari, 2024). A significant growth in both pilot projects and commercial demonstrations, including industrial facilities, is exemplified by large-scale deployments such as the Fukushima Hydrogen Energy Research Field, which produces green hydrogen from solar energy (JapanGov, 2021).

Despite these advances, hydrogen energy systems present significant technical and operational challenges due to their multi-domain nature. First of all, there is a need for efficient storage technologies and dynamic interactions between production, conversion and end-use subsystems (Kamran, 2024). Second, its design and operation are complex due to their multi-domain nature, non-linear dynamics and strong dependency on external conditions such as renewable generation, demand profiles, and operational constraints. These challenges drive to solutions to ensure safe, efficient and low-carbon operation through the application of advanced analysis and control approaches capable of capturing system interactions across multiple time scales and operating scenarios. Conventional modelling and management approaches frequently lack the capability to capture complex system dynamics under diverse operating conditions, constraining systematic performance assessment and optimization.

Under this perspective, digital twins (DTs) arise as a research initiative for hydrogen systems and this solution has expanded rapidly. In this work, a DT is defined as a dynamic digital representation of a physical system that combines data-driven and model-based components to replicate system behavior, support simulation under varying conditions, and enable decision-making through virtual experimentation.

Its main motivation is the need for a safer operation, higher reliability and scalable deployment across the hydrogen value chain (Naanani, 2025). Recent works show how hydrogen DTs are increasingly used for monitoring, anomaly detection, and risk-informed operation, but also stress the ongoing challenges of model fidelity, data availability, and real-time integration across heterogeneous subsystems (Naanani, 2025). Some works, for instance, some DT methods have been proposed to support operational decision-making for electrolyzers. They combine structured modelling workflows with plant data to maintain alignment between the virtual and physical assets (Monopoli, 2024). Beyond single assets modelling, architecture-level DT concepts have been introduced for fleets of electrolyzers (Alsharif, 2024), enabling unified data management and scalable analytics across distributed hydrogen production units.

Scaling up the asset perspective, some studies focus on facility level. These works demonstrate DT modelling for integrated hydrogen energy systems, coupling electrolysers, fuel cells, hydrogen storage and batteries. This research shows the direction towards holistic, system-level twins suitable for experimentation and control evaluation (Weerakoon, 2025). In the same line, (Alsharif, 2023) proposes software and reference architectures for electrolyser digital twins intended to support scale-up and industrial digitalization.

Complementary to the DTs, experimental platforms and testing and experimentation facilities (TEFs) are gaining importance as environments to validate AI (Artificial Intelligence)-enabled control and operational strategies in realistic, safety-critical conditions. Some EU initiatives explicitly include hydrogen testing platforms within large-scale TEF ecosystems, reflecting the strategic role of experimentation infrastructures for accelerating innovation and deployment (CORDIS, 2025).

However, existing research rarely integrates physics-based and data-driven approaches within a unified framework. In this context, a hybrid digital twin is defined as a digital representation in which physics-based and data-driven models are combined to jointly represent system behavior. This approach leverages the complementary strengths of both paradigms. On the one hand, physics-based models rely on first-principles knowledge, ensuring physical consistency. On the other hand, data-driven models capture complex, non-linear patterns directly from operational or sensor data through adaptive learning mechanisms. By combining both approaches, hybrid digital twins can improve predictive accuracy, computational efficiency, and robustness, particularly in scenarios where neither modelling paradigm alone is sufficient (Hunde, 2025). Within this work, hybridization is implemented at component level, where different modelling paradigms are assigned to system components depending on data availability and physical knowledge.

According to (Langlotz, 2022), these hybrid methodologies follow a sequential integration. Data-driven modules perform adjustments or corrections thanks to the physics models. By coupling both frameworks, the active interaction between models is enabled (Langlotz, 2022). Moreover, hybrid modeling facilitates real-time monitoring, predictive analytics and performance optimization by continually updating models with real-world data while constrained by governing physical laws, thus enhancing reliability in complex systems (ANSYS, 2024). Hybrid analysis further show that embedding physics knowledge can reduce uncertainty and improve generalizability of data-driven predictions (Pawar, 2021).

Despite these advances, existing digital twin approaches for hydrogen systems and TEFs remain limited in their ability to support systematic, performance-based evaluation of control strategies within testing and experimentation facilities. Although efforts are put in place, current implementations typically focus on either physics-based simulation or data-driven analytics, with limited integration between both paradigms. Moreover, many DT solutions prioritize monitoring or fault detection rather than scenario-based experimentation, and they often rely predominantly on time-series data while underutilizing contextual information such as system configurations, operational modes, and boundary conditions. As a result, the potential of digital twins as virtual experimentation environments for control strategy assessment and iterative performance improvement remains largely underexplored. Additionally, existing research on hydrogen digital twins addresses different levels of granularity, ranging from detailed component-level models, such as electrolyzers, to system-level representations of integrated hydrogen energy facilities. While component-focused approaches enable high-fidelity modeling of specific assets, system-level digital twins aim to capture interactions across multiple subsystems, albeit often at the expense of detailed component dynamics. Nevertheless, no works are represented in the coupling of multi-level granularity.

Keep in mind these gaps, this paper addresses these challenges by proposing a conceptual hybrid digital twin framework for hydrogen-based testing and experimentation facilities. The proposed approach integrates physics-based and data-driven models and explicitly combines time-series and contextual data to enable scenario-based experimentation and performance-oriented control evaluation. Rather than presenting experimental results, this work focuses on defining a scalable and modular digital twin architecture that supports performance-based feedback loops and systematic comparison of control strategies. Moreover, this work combines multiple levels of granularity, while modelling single components, optimization algorithms combined them to provide a whole system recommendation for optimal operation. The lasting contribution of this paper lies in establishing a foundation for future implementation and validation of adaptive, energy-efficient, and low-carbon control solutions within hydrogen testing and experimentation environments.

The rest of the paper is organized as follows. First of all, the hydrogen-based testing facility is described. Next, the digital twin concept is explained, with the detailed approach that is the contribution in this paper. Following, the combined data sources, time-series and contextual information, are explained as the foundation of the digital twin. Finally, the discussion and conclusions section is stated.

Hydrogen-based testing facility

Hydrogen-based testing and experimentation facilities are designed to provide controlled, flexible and safe environments for the development, validation, and assessment of hydrogen technologies and operational strategies. By the integration of multiple energy systems (both generation and consumption assets and storage subsystems) with AI-driven management strategies, it is enabled the experimentation under realistic operating conditions, taking into consideration real-time data and operation conditions. At the same, safety and regulatory constraints are applied. Their modular and configurable nature makes them particularly suitable for evaluating advanced control approaches, system interactions, and scenario-based operational strategies.

The hydrogen-based testing facility considered in this work couples electrical, hydrogen and thermal subsystems in order to emulate the operation of a smallscale, multi-domain hydrogen energy system. The facility is designed to support experimentation under different operating configurations while respecting safety, power, and communication constraints inherent to laboratory-scale infrastructures.

The hydrogen testing facility is located in the CARTIF technology center building, placed in Valladolid (Spain). Figure 1 illustrates the facilities.

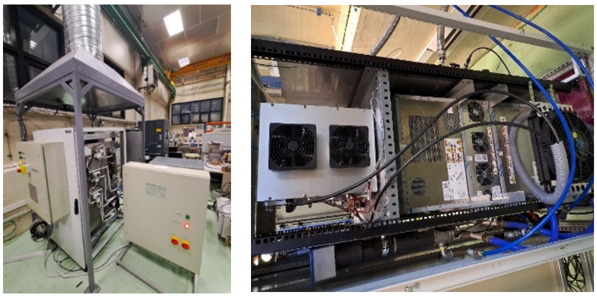

Figure 1: Hydrogen testing system in CARTIF building

The facility is centered on an AEM (Anion Exchange Membrane) electrolyzer with a hydrogen production capacity of up to 500 Nl/h (1.08 kg/day) and nominal power consumption between 2 and 3 kW, operating at pressures up to 35 bar. Hydrogen conversion is supported by a 2 kW PEM fuel cell, enabling cogeneration with fast start-up and flexible load response. The electrolyzer operates within a defined power range, introducing minimum power constraints that are representative of real-world hydrogen production systems. The installation includes metal hydride hydrogen storage, providing a storage capacity of approximately 1.6 kg.

The electrical subsystem provides power conversion bidirectional DC/DC converters. These converters couple the fuel cell output to the electrical bus, enabling regulated power delivery from hydrogen-based electricity generation. This subsystem also includes electrical energy storage in form of lithium-based batteries with a nominal capacity of approximately 2.56 kWh and a nominal voltage of 25.6 V. These batteries support high charge and discharge currents, enabling short-term buffering and fast dynamic response during experimental scenarios. Finally, electronic loads allow controlled consumption of electrical power to reproduce variable demand profiles.

The thermal subsystem provides additional flexibility for future experimentation involving thermal energy management. It includes a heat pump capable of delivering both heating and cooling, as well as an electrically heated water storage tank with a capacity of 300 liters. The thermal assets allow partial coupling between electrical, hydrogen, and thermal domains, supporting future extensions of the digital twin towards integrated energy management scenarios.

The facility is also equipped with an advanced data acquisition and control system based on PLCs (Programmable Logic Controller) and Node-RED communicating with all main components (electrolyzer, fuel cell, hydride tank, batteries, and heat pump). It allows real-time monitoring of parameters such as temperature, pressure, flow, current, and voltage, as well as the implementation of AI-based predictive and adaptive control strategies.

This hydrogen-based system is designed to operate under multiple configurations and operating modes, allowing flexible interaction between subsystems. Hydrogen can be produced stored, or converted back to electricity depending on system conditions, control objectives, and external inputs such as renewable generation and demand profiles. Electrical and thermal loads can be varied to represent different usage patterns, while storage systems provide buffering and flexibility across time scales. This multi-domain interaction introduces non-linear dynamics and strong coupling effects, which are characteristic of real-world hydrogen energy systems. In this sense, the system can reproduce variable generation and demand profiles, enabling the study of renewable integration, load shifting, and storage optimization at building and microgrid scales. For that reasons, the facility supports scenario-based analysis by enabling controlled variation of boundary conditions, system configurations, and control strategies. Forecasts of renewable generation and energy demand can be incorporated to emulate prospective operational scenarios.

Last but not least, the constraints should be taken into account. Minimum and maximum power limits for the electrolyzer, DC/DC converters, and power supply, a maximum system power rating of 2 kW, limited configurability of battery electrical connections, and the absence of direct control over fuel cell internal operating parameters. Additionally, communication limitations between certain components introduce non-ideal behaviors, which further motivate the use of digital twin-based experimentation to evaluate control strategies under realistic conditions.

In short, this hydrogen-based testing facility provides the physical foundation for the digital twin framework proposed in this paper. Its modular structure, multi-domain nature, and configurable operation make it well suited for investigating performance-based control evaluation, system-level interactions, and feedback-driven optimization through virtual experimentation.

Hybrid digital twin for performance-based control evaluation

The complexity and multi-domain interactions of hydrogen-based testing facilities require advanced digital representations capable of supporting systematic control analysis beyond conventional simulation approaches. In this context, hybrid digital twins emerge as an effective solution by combining physics-based models with data-driven components to capture both system dynamics and operational variability. This section introduces the proposed hybrid digital twin framework, designed to enable performance-based evaluation of control strategies through scenario-based experimentation. By integrating time-series and contextual data, the digital twin provides a virtual environment for analyzing control performance, exploring alternative operational configurations, and supporting feedback-driven decision-making without interfering with real facility operation.

Digital twin conceptual approach

Figure 2 illustrates the conceptual approach of the proposed hybrid digital twin. The digital twin is fed with two data inputs: trained models and real time data. The models are trained using both time-series and contextual data to provide component-level models to be operated with the AI algorithms. The outputs of this process include control strategies and performance indicators used for evaluating operational configurations to compare the original strategy and the AI-based one, as indicated in Figure 4.

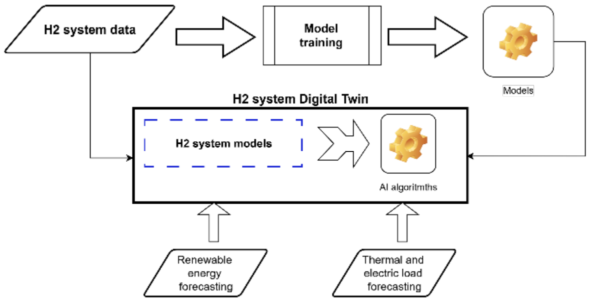

Figure 2: Digital twin conceptual approach

Entering into details, at the top level, historical, operational and contextual H_2 system data are collected from the testing facility and used within the model training process. This stage is responsible for preparing and calibrating the digital representations of the physical system. These digital representations are implemented at component level (see next section for more details). These models include both physics-based and data-driven details. The outcome of this process is a set of validated models that capture the dynamic behavior of the hydrogen system under different operating conditions.

The lower layer represents the operational digital twin, where the trained models are instantiated as H_2 system. Combined with AI-based algorithms, optimal configuration and parametrization can be obtained. Scenario-based experimentation is thus enabled through the integration of renewable energy forecasting and thermal and electrical load forecasting to determine future conditions of the operational stage. These external inputs provide prospective boundary conditions to the digital twin, allowing the evaluation of control strategies under varying demand and generation profiles.

By decoupling model training from operational experimentation and embedding forecast-driven scenarios, the proposed digital twin supports systematic and repeatable evaluation of control strategies. This structure enables performance-based comparison of alternative control approaches and establishes the foundation for feedback-driven optimization and future adaptive control deployment in hydrogen testing and experimentation facilities.

Detailed digital twin components

As explained previously, the proposed hybrid digital twin is composed of a set of modular, component-level models that collectively represent the behavior of the hydrogen-

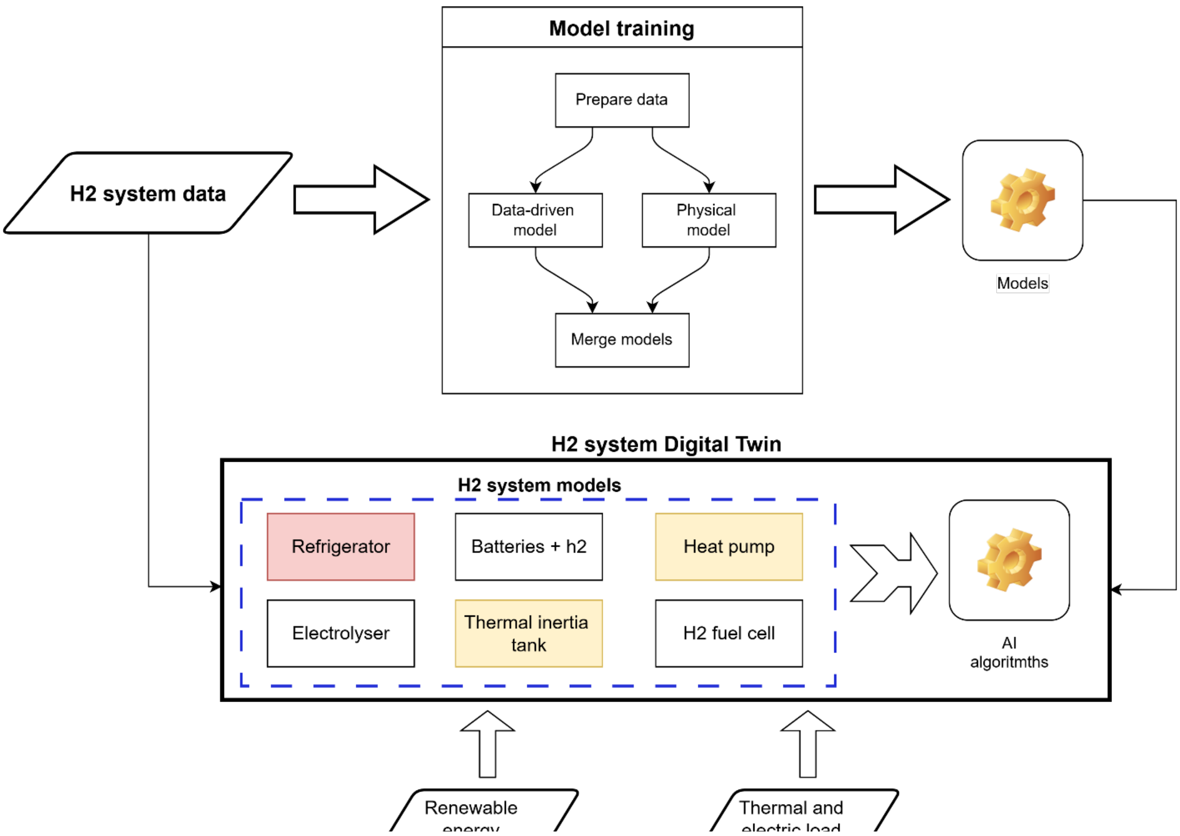

Figure 3: Detailed configuration of the digital twin for the H_2 facilities

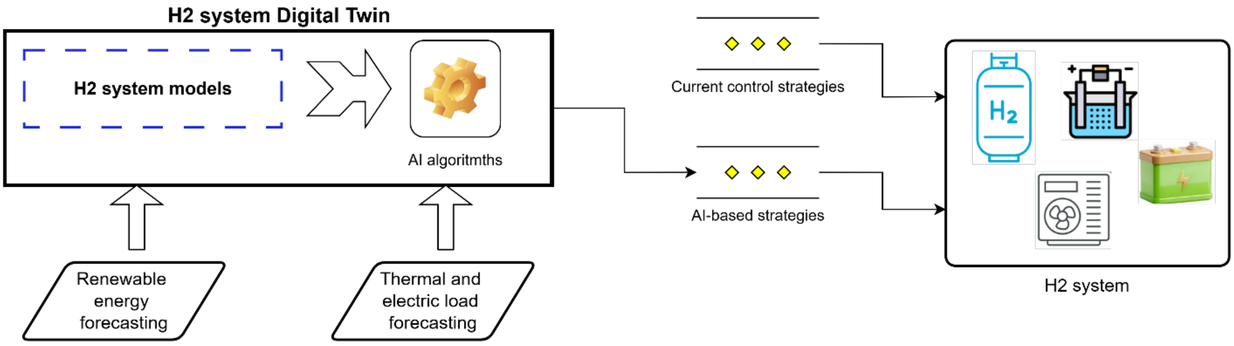

Figure 4: Comparative operational strategies for performance-based control scenarios

based testing facility. These models correspond to the main subsystems of the facility, including hydrogen production, storage, conversion, and associated electrical and thermal components. Within this layer, the digital twin operates as a virtual experimentation environment, enabling the execution of multiple scenarios without interfering with real system operation.

Figure 3 illustrates how the different component-level models are grouped and how they interact with AI-based algorithms to support scenario-based control evaluation. Each digital twin component captures the dynamic behavior and operational constraints of a specific physical asset, while their coordinated integration enables system-level analysis across electrical, hydrogen, and thermal domains for a system-level analysis.

In Figure 3, the color coding is used to explicitly represent the hybrid modelling approach adopted in the proposed digital twin.

Red components correspond to mathematical or estimation-based models, which is used for the refrigerator. The reason for this approach relates to the lack of real physical assets, while the estimation of the amount of energy used for refrigeration is estimated via indirect measurements. This allows to approximate system behavior by estimations.

Yellow components denote physics-based models derived from first-principles formulations. In the proposed architecture, this approach is adopted for the heat pump and the thermal inertia tank, where thermodynamic relationships are used to represent heat generation, storage, and dissipation processes. The use of physics-based models in these assets is motivated by the limited availability of real-time operational data.

Finally, white components represent data-driven models trained directly from historical and operational data. This modelling approach is applied to the electrolyzer, batteries, hydrogen storage system, and fuel cell, for which sufficient experimental data are available from real operation. These models capture complex, non-linear behaviors and component-specific dynamics that are difficult to describe analytically.

By combining mathematical estimations, physics-based representations, and data-driven models within a unified framework, the proposed digital twin achieves a balanced trade-off between model fidelity, adaptability, and computational efficiency. This hybrid structure enables systematic, performance-based evaluation and comparison of control strategies under forecast-driven operating conditions.

Performance-based strategies comparison

Figure 4 illustrates how the proposed hybrid digital twin is used to support performance-based comparison of alternative control strategies. In this stage, the integrated H_2 system models are coupled with AI-based algorithms. These AI algorithms interact with the system models to generate control actions, assess system responses, and compute performance indicators related to efficiency, energy balance, and operational feasibility. These algorithms include model predictive control (MPC) or reinforcement learning (RL).

To further formalize the control evaluation process, the problem addressed by the digital twin can be formulated as a constrained optimization problem. The objective is to minimize energy consumption from the grid, while maximizing renewable energy use and system efficiency. This can be expressed as:

$$\min\left(\alpha_1 \cdot E_{grid} + \alpha_2 \cdot C_{oper} + \alpha_3 \cdot H_{2\_loss}\right) \tag{2}$$

where, E_{grid} is the energy supplied by the grid, C_{oper} is the cost of the operation and H_{2_loss} is hydrogen losses.

Scenario definition is driven by renewable energy forecasting and thermal and electrical load forecasting, which provide prospective boundary conditions for system operation. These forecasts allow the digital twin to emulate future operating conditions, such as variations in renewable generation availability and demand profiles. For each scenario, AI algorithms determine control actions related to hydrogen production, storage usage, energy conversion, and subsystem coordination.

Each candidate control strategy is executed within the digital twin, where the system response is simulated at component level and, then, aggregated at system level. Performance indicators are computed based on predefined metrics, split into three groups: model calibration, AI-based predictive control and hybrid energy integration and flexibility.

Table *1*,

Table 2 and Table 3 summarizes these Key Performance Indicators (KPIs) with the baseline (monitored before the implementation of the DT) and target values to be achieved by the application of the digital twin. By repeating this process across multiple scenarios and strategies, the digital twin enables objective, quantitative comparison of alternative control approaches.

Table 1: KPIs for the model calibration

KPI	KPI description	Baseline	Target value
Model accuracy index	Quantifies deviations between simulated and experimental variables.	±10% average deviation	< ±5% deviation across all monitored variables
System response time	Time to reach steady state after a setpoint change.	> 60s average	< 30s for 90% of test cases
Operational data completeness	Proportion of data successfully integrated into the AI data lake.	85% completeness	≥ 95% completeness

Table 2: KPIs for the AI-based predictive control

KPI	KPI description	Baseline*	Target value
Prediction accuracy of AI models	Measures forecasting error for energy demand and hydrogen production	MAE = 0.15	MAE ≤ 0.05
Energy cost reduction through AI control	Quantifies reduction in energy consumption.	0%	≥ 10% reduction
Renewable energy utilization rate	Ratio of renewable input energy used in hydrogen production.	70%	≥ 90%
Ratio H2 stored energy vs renewable	Ratio of energy stored in the H2 system versus the renewable input energy.	n.a.	> 65%
Ratio battery stored energy vs renewable	Ratio of energy stored in the batteries versus the renewable input energy.	n.a.	> 30%
Ratio H2 cell energy vs energy demand	Ratio of energy generated by the H2 cell versus the energy that is demanded.	n.a.	< 30%
Net consumed energy	Energy that is used from the grid.	n.a.	
Hydrogen storage cycle efficiency	Ratio between energy recovered and energy input per cycle.	80%	≥ 90%

** n.a. refers no baseline is available, just a target value to be achieved with the implementation of the DT.*

Table 3: KPIs for the hybrid energy integration and flexibility

KPI	KPI description	Baseline	Target value
System flexibility index	Ability of the integrated system to adapt to variable generation and demand.	Flexibility ratio = 0.6	≥ 0.85
Thermal–electrical coupling efficiency	Performance of heat recovery and utilization in cogeneration mode.	70%	≥ 85%

The outcomes of this comparison process support the identification of control strategies that best satisfy performance objectives and operational constraints. Moreover, the results provide structured feedback for refining control logic and parameterization, establishing the basis for performance-driven optimization and future adaptive control deployment within hydrogen testing and experimentation facilities.

Time-series and contextual data integration

The effectiveness of the proposed hybrid digital twin relies on the coherent, explicit and structured integration of time-series and contextual data originating from the hydrogen-based testing facility. This approach ensures ensure consistent model instantiation, execution, and evaluation. Unlike conventional approaches that treat operational data in isolation, this work defines a unified data representation in which dynamic system behavior and static system description are jointly exploited within the digital twin lifecycle. The proposed architecture is drawn in Figure 5, where both data types are managed through a data lake-oriented approach, ensuring continuous synchronization between them.

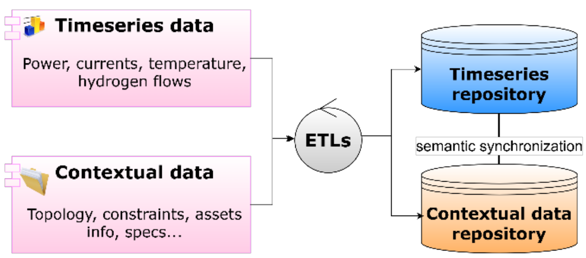

Figure 5: Integration of time-series and contextual data for hybrid digital twin execution

Data typology and roles

Time-series data represent the dynamic evolution of the hydrogen-based testing facility and consist of high-frequency measurements acquired from the physical system. These include electrical variables (power, current, voltage), thermodynamic variables (temperature, pressure), hydrogen flows, and state variables such as battery state of charge or hydrogen storage level. Additionally, forecasted inputs, including renewable generation and thermal and electrical demand profiles, are incorporated as time-dependent boundary conditions for scenario-based experimentation.

In contrast, contextual data provide the structural and semantic description of the system. This includes asset definitions (e.g., electrolyzer, fuel cell, storage units), system topology, operational constraints (e.g., power limits, pressure thresholds), nominal capacities, and configuration parameters. Contextual data also define the relationships between variables and assets, enabling the correct interpretation of measurements and ensuring consistency across models and scenarios.

This integration enables the digital twin to instantiate component-level models with the correct configuration and constraints while being continuously driven by dynamic operational data and forecasted inputs. During scenario-based experimentation, contextual data define the system configuration and control boundaries, while time-series and forecasted data provide evolving boundary conditions. As a result, the digital twin can execute reproducible simulations, evaluate control strategies under varying conditions, and compute performance indicators in a consistent and traceable way.

By combining time-series and contextual data within a unified and governed data infrastructure, the proposed approach ensures that digital twin simulations remain physically meaningful, adaptable to changing conditions, and suitable for systematic performance-based control evaluation in hydrogen TEFs.

Data model and semantic mapping

To enable integration, both data types are represented through a shared data model based on three core entities: assets, variables and observations. Each asset (e.g., electrolyzer) is associated with a set of variables (e.g., input power, hydrogen production rate), which are linked to time-series observations through unique identifiers. Contextual data define the attributes and constraints of each asset, while time-series data provide their temporal evolution. Formally, a time-series observation can be represented as the equation (2):

$$o = (a_i, v_j, t_k, x_{ijk}) \qquad (2)$$

where, a_i is the asset, v_j is the associated variable, t_k the timestamp and x_{ijk} the measured or forecasted value. Contextual data define the admissible domain of the measurement, as well as the relationships between variables across assets.

This mapping enables the digital twin to interpret each data point within its physical and operational context, avoiding ambiguity and ensuring that model inputs are aligned with system constraints.

Integration and synchronization mechanism

While time-series data are stored in a repository optimized for temporal queries, contextual data are maintained in a structured repository capturing system configuration and semantics. Therefore, a synchronization mechanism is required to both repositories through:

- shared asset identifiers,
- timestamp alignment for dynamic data,
- semantic tagging of variables and units.

The data model is designed to be compatible with semantic standards such as SAREF and SAREF4ENER, enabling formalized representation of assets, variables, and their relationships, and supporting scalable and interoperable digital twin implementations.

This process ensures that each time-series input used by the digital twin is consistently mapped to its corresponding asset and variable definition. Furthermore, updates in contextual data (e.g., configuration changes or operational constraints) are propagated to the digital twin to ensure that simulations reflect the current system state.

This integrated approach enables the digital twin to operate in two complementary modes: model instantiation and scenario execution. During model instantiation, contextual data are used to configure component-level models, defining parameters such as capacities, limits, and connectivity between subsystems. During scenario execution, time-series data and forecasted inputs drive the dynamic behavior of the models, providing evolving boundary conditions.

Discussion and conclusions

This paper has presented a conceptual hybrid digital twin framework for hydrogen-based testing and experimentation facilities, aimed at enabling performance-based evaluation of control strategies under realistic and forecast-driven operating scenarios. The proposed approach addresses key limitations identified in the current state of the art, namely the fragmented use of physics-based and data-driven models, the limited exploitation of contextual data and the lack of systematic support for scenario-based control comparison within testing environments.

By combining component-level digital twins with multiple modelling paradigms, such as mathematical estimations, physics-based representations, and data-driven models, the proposed framework achieves a balanced trade-off between physical fidelity, adaptability, and computational efficiency. This hybrid structure allows the digital twin to capture both the dynamic behavior of hydrogen systems and the operational constraints imposed by real testing facilities. The explicit integration of time-series and contextual data further ensures consistency, traceability, and reproducibility across scenarios, which is essential for meaningful performance-based control evaluation.

The framework has been designed with a strong focus on modularity and scalability, enabling its application across different levels of granularity, from individual components to integrated multi-energy systems. In this sense, the digital twin acts as a virtual experimentation environment, supporting the systematic comparison of alternative control strategies based on clearly defined performance indicators. Although no experimental validation results are presented in this work, the proposed architecture establishes the necessary foundations for structured experimentation, optimization and decision support in hydrogen TEFs.

Future work will focus on the implementation and experimental validation of the proposed hybrid digital twin within the CARTIF hydrogen testing facility. This includes the deployment of the component-level models, the integration of real-time data streams, and the execution of representative operational scenarios to assess the effectiveness of different AI-based control strategies. Further developments will address the extension of the control layer towards closed-loop adaptive operation, the calculation of performance indicators, and the inclusion of additional assets and use cases. In the longer term, the proposed framework will be evaluated for scalability and transferability to other hydrogen-based facilities and multi-energy systems within large-scale testing and experimentation infrastructures.

Acknowledgments

This work has been done under the EU funded project EnergyGuard (Large-Scale Testing and Experimentation Facility (TEF) for Assessing, Validating, and Enhancing AI-Powered Next-Generation Energy Solutions), under Grant Agreement 101172705. The authors would like to thank the rest of the contributing partners of the project for the support and help in the developing of the work.

During the preparation of this work the authors used DeepL and ChatGPT in order to improve the grammar and readability of some sentences. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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