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Adaptive Energy Management and Data-Driven Multi-Objective Optimization of Hybrid PV-Hydrogen Storage Systems for Off-Grid and Microgrid Applications

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Abstract - **With the growing penetration of renewable resources in off-grid and microgrid areas, energy management strategies need to be developed and implemented to cope with intermittency, storage constraints and multi-objective operational requirements. In this paper, we build an adaptive energy management and data-driven multi-objective optimization framework for hybrid photovoltaic (PV)–hydrogen storage systems consisting of electrolyzers, hydrogen storage tanks, and fuel cells. In this case, the primary goal is maximizing overall system performance and renewable energy utilization with minimal operational cost, energy losses, and component degradation under dynamic environmental and load conditions. The approach uses a hybrid data-driven optimization structure which merges predictive models with real time adaptive control. To achieve this, a multi-objective optimization problem is established to optimize key performance indicators (KPI), such as energy efficiency, hydrogen production/consumption balance, SOC regulation and system reliability at the same time. A predictive model-based machine learning method is integrated into the multi-agent framework to foretell solar generation, load demand and thermal unit states in order to handle system uncertainties and nonlinear dynamics. This is combined with an adaptive decision-making layer that continually modulates the power balance between PV generation, hydrogen production (with electrolysis), storage and reconversion through fuel cells.**

Such a multi-objective optimization framework is constructed to solve the problem providing Pareto-optimal solutions with trade-offs between contradicting objectives e.g. in cost reduction vs efficiency maximization. In addition to this, a supervisory control mechanism is also employed in real time that guarantees the system stability and constraint satisfaction on hydrogen storage tank limits, fuel cell operation limits and power balance conditions.

The simulation studies have been performed for a variety of operating conditions such as different solar irradiance profiles, stochastic load demand, off-grid/microgrid. The results show that the proposed approach achieves an energy utilization efficiency improvement between 28–35%, operational cost reduction of 20–25% and improvements in system reliability compared to conventional rule-based and deterministic optimization solutions. Also, the adaptive framework is effective at reducing energy curtailment and manages optimal hydrogen consumption, ensuring uninterrupted supplies during low-generation periods. Findings exhibited the promise for a synergistic integration of data-driven intelligence and multi-objective optimization for next-gen hybrid renewable energy systems. The Task Method based Distributed Framework will open the way towards a scalable and reliable off-grid and micro-grid solution that would contribute to sustainable energy, energy autonomy, and resilience.

Keywords— **Hybrid PV–hydrogen energy systems; Multi-objective optimization; Adaptive energy management; Data-driven control; Off-grid and microgrid systems; Renewable energy storage.**

I. INTRODUCTION:

With the global shift towards low-carbon and sustainable energy systems, renewable energy technologies have been increasingly deployed and among them, photovoltaic (PV) systems have gained significant attention because they are a modular, scalable solution with rapidly declining installation costs. Photovoltaic (PV) based generation has rapidly established a base in the energy infrastructure of modern capacity developments, increasingly utilized in off-grid and microgrid applications as a clean decentralized alternative to traditional fossil-fuel-based power systems. However, despite above advantages, due to the intermittent and stochastic nature of solar irradiance causing significant challenges for maintaining power balance, voltage stability and supply reliability, particularly in isolated or weak grid scenarios [1], [2]. Intense solar energy, the technology and core of that strategy, has variability associated with it leading to mismatch between generation-demand or vice-versa which causes curtailing of power at peak hours of generations whilst there is high availability for storage and also during low irradiance conditions where theoretically you may have expected higher load on grid but ultimately end up facing power crisis. In off-grid and microgrid systems, the lack of a strong grid connection to balance fluctuations makes these challenges even more salient. Thus, the utilization of energy storage systems (ESS) was developed as integral for system flexibility gains and continuous energy supply, as well as enabling high penetration of renewable resources [3]. Of the various storage technologies, hydrogen energy storage systems (HESS) have become an attractive technology for long-term and large-scale storge systems. Hydrogen storage differs from conventional battery systems, which are more appropriate for short-term energy balancing as hydrogen boasts a higher energy density and a much longer storage duration with low self-discharge, all properties making it more attractive for seasonal and long-duration applications [4], [5].

Electrolysis can use surplus PV energy to make hydrogen, which is then stored compressed or liquefied and later fed back into fuel cells for electricity generation when required. This process helps with the decoupling of energy generation and consumption hence increasing the reliability of systems and their operational flexibility. What you find in a hybrid PV–hydrogen energy system is the combination of PV and electrolyzer, then hydrogen storage bunker and power generators such as fuel cells which create electrical power. When there is generation surplus the overgeneration amount of PV power directly goes to the electrolyzer producing hydrogen stored for later. When solar generation is insufficient at times, the hydrogen stored in the storage tank will be turned back into electricity via fuel cells to meet load demand. The integrated structure allows an energy shifting between time scales, enhancing the utilization of renewable resources and minimizing dependence on backup diesel generators or grid electricity imports [6], [7]. Integrating hydrogen storage systems in microgrids has been proven to increase the resilience, autonomy and sustainability of microgrids. Numerous studies have reported that hybrid PV–hydrogen systems can provide nearly 100% reliability with zero emissions under a variety of operating conditions [8]. In addition, hydrogen-based systems favor sector coupling, as they can easily be implemented in other energy sectors (e.g., transportation, industrial process) and considered within a broader framework of the energy transition [9]. Simultaneously with progress in master architecture, huge investigation has been led for the improvement of energy management systems (EMS) and optimization methodologies for half breed sustainable energy provided frameworks. The EMS manages energy flows between generation, storage and load to provide efficient and reliable operation. Traditional EMS approaches such as rule-based control and deterministic optimization have been popular; however, their performance is often constrained by their inability to adapt to dynamic and uncertain operating conditions [10]. In order to address these deficiencies, multi-objective optimization techniques have gained popularity in recent years. These approaches allow comparative optimization of multiple performance criteria including energy efficiency, operational cost, emissions reduction, system reliability and component degradation. One such is the evolutionary algorithm where researchers have applied it along with other techniques like Particle swarm optimization and Pareto-based methods for designing optimal trade offs between conflicting objectives [11], [12]. This is particularly important for hybrid PV–hydrogen systems, where the decision involves finding the right trade-offs between a short-term performance and long-term sustainability and economic viability, which may be treated by multi-objective frameworks. However, with hybrid technology systems becoming more complex and subject to uncertainty, it calls for advanced, adaptive and data driven methods. Machine learning and smart optimization methods can now be integrated to exploit new possibilities for system performance enhancement, including real-time decision-making and robustness improvement under uncertainty [13], [14]. To sum up, hybrid PV–H2 storage system is a promising solution for remote renewable energy integration when not grid connected (e.g. off-grid or microgrid applications) 4. This integrated renewable generation, along with long-term energy storage and advanced energy management strategies, provides a roadmap to reliable, efficient and sustainable energy systems. Nevertheless, to exploit the full potential of these systems, adaptive, multi-objective, and data-driven optimization frameworks need to be devised — the core theme of this work.

However, despite the rapid advances in hybrid renewable energy systems, optimal energy management in large-scale and complex hybrid PV–hydrogen storage systems are not only highly cited but still an unresolved challenge in the literature [15]. This challenge stems from the multi-objective requirement of simultaneously meeting conflicting objectives such as maximizing renewable energy utilization, minimising operation & lifecycle costs, ensuring system reliability and lifetime extension of key individual components (e.g. electrolyzer, fuel cell, storage). These are inherently interdependent, and more often than not contradictory objectives. To illustrate, running electrolyzer at high capacity for hydrogen production may increase the use of renewables, however deteriorated components as a consequence [16] increased maintenance or cost thus representing its drawbacks. Likewise, approaches based on minimization of costs may result in lower system reliability or a decrease in efficiency of conversion processes. Besides parametrical multi-objective trade-offs, hybrid PV–hydrogen systems function within environments characterised by extreme uncertainty and dynamic evolvement. The basically intermittent nature of solar irradiance, the seasonal and geographical variability and weather impact introduce unpredictability in PV power generation profiles. At the same time, in an off-grid and microgrid network environment the load demand is driven stochastically with random characteristics determined by consumer behavior or external factors. These uncertainties lead to serious difficulties in the power balance and stable operation of the system [17]. Also, system component dynamics are both nonlinear and coupled, which makes control and optimization very difficult. All of the dynamics are nonlinear with respect to efficiency, delay times and bounds on instantaneous input parameters for electrolysis, hydrogen compression, storage and fuel cells [18]. The slow dynamics of hydrogen-based subsystems and their moderate ramping capabilities add extra levels of complexity. Electrolyzers and fuel cells, in contrast with battery storage systems which have a nearly instantaneous response time, function under certain limits of dynamics or operation that prohibit their use when there is a rapid ramp-up or down of power characteristic associated with wind or other variable renewable energy (VRE) sources. The rapid variability of the PV output and the slow response of hydrogen system can create inefficiency, energy loss and inappropriate usage of resources [19]. As a result, traditional deterministic and rule-based energy management strategies, which are based on rigid operating rules or simplified models, frequently cannot sustain the optimal performance throughout such time-varying and uncertain conditions. A significant aspect of the problem is the hybrid PV–hydrogen system nature whose composition permits interactions over a variety of timescales. From real-time control (e.g., seconds to minutes) for balancing power flows, short-term scheduling (e.g., hours to days) for energy optimizing, and long-term planning (e.g., weeks to months) for resource allocation and system optimization. The above decision layers have a tightly coupled dependency structure but current approaches [20] work only in isolation to model and optimize these decisions, which results in poor coordination between layers leading to inefficiencies. The integration of these multi-timescale decision in a unified framework is particularly difficult under uncertainty given the need for forecasting, adaptive control, and computationally efficient optimization algorithms that must span different time horizons. In addition, traditional energy management systems are not designed to learn and adapt, which only compounds these problems. Most current methods are based on static models with designed operating conditions, which cannot cope well with evolving system dynamics over time, environmental perturbations and component aging. This is important, as the performance of the system deteriorates over time, and what was once an optimised energy management strategy might become suboptimal (or even impractical) due to changing conditions [21]. In conclusion, the core challenge in hybrid PV–hydrogen energy management is to formulate such a cohesive and computationally light model capable of solving multi-objective optimization, system uncertainty, nonlinear dynamics and multitimescale decision-making. Most of extant approaches are either centered on local optimization of the timing or an individual edge, thus leading to piecemeal solutions that do not guarantee global optimality. This challenge calls for adaptive, data-driven, and integrated optimization frameworks that can balance competing objectives while retaining robust performance under operational realities.

In spite of the increasing literature on hybrid PV–hydrogen energy systems, the issue of optimal, reliable, and adaptive energy management has not yet been solved due to numerous interrelated technical and methodological problems [22]. One major reason is the inherent complexity and strong nonlinearity in these systems. Hybrid PV–hydrogen architectures consist of closely integrated electrical, electrochemical, and thermodynamic processes, namely PV generation, electrolytic water-splitting for green hydrogen production as well as compressed pseudo-liquid H2 storage capacities together with fuel cells to yield integrated system approaches. All of these subsystems are characterized by nonlinear input–output relationships, time-varying efficiencies, and operational constraints. Electrolyzers and fuel cells exhibit nonlinear efficiency curves based on entropic load, temperature, and degradation states, whereas hydrogen storage entails pressure–volume nonlinearities as well as safety constraints. Consequently, the streamlined or linearized models used in control design do not faithfully capture system dynamics; resulting in non-optimal and/or unstable control actions at real operating conditions [23]. Furthermore, environmental and load uncertainty creates even more challenges. Solar irradiance is by nature stochastic and highly dependent on weather conditions, cloud coverage, and seasonal cycles; in off-grid (and even microgrid) networks, load demand often presents an unpredictable but extremely dynamic behaviour. Such uncertainties carry through the layers of the system, impacting short-term operational choices and long-term planning. Conventional energy management systems (EMS) often utilise deterministic forecasts or average profiles instead, missing the inherent variability in reality. As a result, these methods underperform, lead to energy imbalance and waste computer resources when deployed in real-world environments [24]. Many of currently established optimization and control strategies are highly dependent on correctly defining the system model, which presents another major limitation. Techniques like model predictive control (MPC), dynamic programming, and optimization-based EMS frameworks rely on accurate mathematical models of the system. But, the standardized models for hybrid PV–hydrogen systems are intrinsically hard to get as a result of parameter uncertainty, component ageing, environmental effects and unmodeled dynamics. As time advances, deviation between what has been modeled against the actual system idiosyncrasy or mechanically described phenomenon—a term is generally given as model mismatch—decreases control performance, creates inefficiency and gives rise to unreliability of the system [25]. The computational complexity of multi-objective optimization also presents a significant impediment to real-time use. Hybrid PV–hydrogen systems necessitate the simultaneous optimization of several objectives (cost, efficiency, reliability, and component lifespan) with numerous operational constraints. Often the optimization problems one tries to solve are high-dimensional, nonlinear and non-convex leading to a computationally intensive workout. Evolutionary Algorithms (EAs) and some metaheuristic methods can indeed explore solution spaces well; however, their computational cost makes them more suitable for tuning purposes than real-time control. This is especially evident in off-grid and microgrid applications where computational resources are often constrained [26]. Additionally, current energy management methods are constrained by their ability to adapt and learn. Many traditional EMS methods are developed with rule-bases, fixed parameters or offline optimization results that hold only under specific operating conditions. These static strategies then lose their effectiveness as system dynamics change due to environmental perturbations, load variations, or component degradation. But the lack of dynamic adaptation to changing conditions restricts their use for real-world applications that require flexibility and responsiveness [27]. Finally, the literature illustrates a compartmentalized optimization approach, while single studies generally optimize individual aspects of system performance (e.g., cost minimization; efficiency improvement; reliability enhancement) rather than addressing all system objectives in an integrated framework. Conversely, without a unified framework, you get solutions that optimize one objective at the cost of others and hence won't be optimal overall or globally. Furthermore, the lack of coordinated strategies which simultaneously address prediction, optimization and control across time scales can amplify this [28]. In this regard, the problem is ongoing due to system nonlinearity and uncertainty, model dependency and computational constraints, no adaptive capability and stand-alone optimization method. This is possible, by means of dedicated integrated, adaptive and data-driven multi-objective optimization frameworks that can execute in an efficient manner throughout the years under uncertainty, while at the same time satisfying conflicting system objectives.

The literature proposes a large spectrum of methodologies to tackle energy management and optimization in hybrid PV–hydrogen systems, each class of approaches shows intrinsic limitations which impede exhaustive and robust solutions [29]. Some of the earliest and most widely used are model-based energy management and optimization approaches such as rule-based control, linear programming (LP), dynamic programming (DP) and model predictive control (MPC). Such strategies utilize mathematical representations of dynamics to optimize energy flows between PV generation, hydrogen production storage and load demand. For example, optimization-based frameworks are applied to find the best operation schedules for both electrolyzer and hydrogen storage under economic as well as operational constraints [30]. In particular, the traditional methods based on model predictive control (MPC) have drawn increasing attention owing to their ability to enforce system constraints while forecasting future trajectories over a finite window. Nevertheless, while they display theoretical optimality through a structured formulation, existing approaches are heavily reliant on accurate system models and forecasts. Performance in real-world settings characterized by uncertainty, model mismatch and forecasting errors can severely limit the usefulness of these methods [31]. Moorhead hinders the work of it in its very own way Test an abstract version and display me through utilizing machine studying systems from TF by giving the purpose TO embrace data less than multi-objective optimization type assert. Simultaneous optimization for conflicting objectives such as energy efficiency, operational cost, emissions and system reliability can be done using methods like genetic algorithms (GA), particle swarm optimization (PSO) and Pareto-based evolutionary algorithms. These methods offer a collection of Pareto-optimal solutions enabling decision makers to choose among suitable trade-offs in accordance with system specifications [32]. Multi-objective optimization has been particularly useful in [33] for improving the performance and sustainability of hybrid PV–hydrogen systems in system design and long-term planning contexts. But these algorithms are mostly computational intensive and their implementations take place in offline domain. Their computational intensity and iterative form make them inapt for real-time control, where prompt adaptive decision-making is vital. At the same time, a large number of studies have examined the coupling of these systems into hybrid energy storage systems especially hydrogen and battery energy storage systems (BESS). This combined configuration utilizes the best of both technology types: batteries provide rapid dynamic response and short-term energy balancing, while hydrogen systems provide long-term storage with higher energy densities. As can be seen in [34], studies have proven that the introduction of such hybrid storage systems can lead to improved microgrid resilience, lower energy curtailment and overall increased system efficiency. However, the coordination of a variety of different storage technologies is far more complex, especially when trying to agree on how each (high-capacity/low-power vs. low-capacity/high-power) will share power in uncertain scenarios and dynamic environments. Coordination strategies are typically based on heuristic or rule-based methods that may fail to provide optimal performance in all operating scenarios [35]. Data-driven and intelligent methods have emerged, more recently, as potential new alternatives to traditional solutions. Machine learning, artificial intelligence, and reinforcement learning techniques allow systems to learn from historic and real-time data rather than relying on explicit system models. As an example, artificial neural network (ANN), the support vector machine (SVM) and deep learning model have been employed for load forecasting [36], renewable energy prediction [36] and hybrid energy systems optimization system designs. These methods provide greater flexibility and resilience, as they are able to model nonlinear relationships and dynamically adapt to new circumstances. Simultaneously, reinforcement learning based frameworks have demonstrated capabilities to learn optimal policies via interacting with the environment for real-time adaptive control. Data-driven approaches show promise for optimizing hybrid PV–hydrogen systems, but remain in relatively early stages of development. One major limitation, however is the non-integrated framework with respect to multi-objective optimization and real-time control. Existing studies mainly concentrate on independent tasks such as prediction or single-objective optimization, without offering a unified architecture that integrates learning, optimization, and control. In addition, data availability concerns (harvesting dataset), training difficulty (great efforts) and model generalization with unseen conditions still remain challenging [37]. In summary, the research discussed here covers important aspects of energy management and optimization for hybrid PV–hydrogen systems, but there is no single method successful on coping with the combined challenges of multi-objective optimization, uncertainty treatment, real-time intelligence and systems integration. Sensitivity of model-based methods on uncertainties, difficulties with solving multi-objective optimization problems, bottlenecks in coordination of hybrid storage systems, and limitations of data-driven approaches (research gap) which are not yet fully coupled with in complete control frameworks. These limitations motivate alternative, adaptive, data-driven and stochastic optimization strategies, which are the cornerstone of the approach adopted in this work.

This paper deals with addressing the gaps that exist in the literature by proposing an adaptive energy managers and data-driven multi-objective optimization framework appropriate for hybrid PV–hydrogen storage systems to work under uncertainty and changing conditions [38]. The idea behind is to shift from traditional model-centric and static optimization methods to a more comprehensive, scalable solution combining intelligence based on data with the option of real-time decisions as well as multiple objective optimized solutions into one architecture. With this integration, the system can respond dynamically to renewable generation and load demand while preserving optimal performance of a multi-objective problem based on variable scenarios across system states. This prediction layer is built on historical data and real-time inputs to predict important system parameters, such as solar irradiance, load demand, and internal system states. This data-driven framework reduces dependence on explicit mathematical models to support robustness and adaptability under model uncertainty and parameter variation. Such predictive ability allows proactive energy management decisions, forecasting future conditions and scheduling appropriate control actions [39]. Based on this prediction layer, a multi-objective optimization framework is established to tackle multiple key performance metrics simultaneously. Therefore, the optimization problem focuses on maximization of renewable energy utilization and overall system efficiency, and minimization of operational costs, energy losses and components degradation. It also includes reliability and system stability as some fundamental objectives, guaranteeing hard performance under various operating conditions. Such multi-objective formulation allows determining the best trade-offs among these conflicting objectives [40], resulting in a more balanced and efficient operational strategy. Instead, an uncertainty-aware control strategy will be incorporated into the proposed framework (Section 4), in order to explicitly consider stochastic uncertainties of both renewable generation and load demand for higher robustness. In contrast to deterministic approaches based on scenarios and fixed forecasts, the proposed method accounts for uncertainty by using probabilistic information along with adaptive decision-making mechanisms in real time. That guarantees that the system can function reliably and time-stably although an unknown input of external factors [41]. The main characteristic of the approach devised is that it can implemented in real-time. Solving Path Planning problem for high dimensional systems inherently presents computationally expensive nature of multi-objective optimization use fast decision-making strategy with the help of efficient algorithms and adaptive control to allow running real time applications, we use learn way more generalizable path planning via adaptive control. The framework will function in off-grid and microgrid systems while remaining computationally efficient to ensure that the optimization, storage and planning problem is tractable [42]. Moreover, the proposed method offers a consolidated coordinated control to PV–hydrogen systems by integrating of PV generation and hydrogen production through electrolysis with the operational planning of storage management and energy reconversion using fuel cells. Such coordinated strategies ensure optimal energy flow through the connected components of a system, leading to improved overall efficiency and a reduction in grid energy curtailment. The framework increases system reliability and allows for perfect energy balancing over several timescales, by coordinating the operations of various subsystems [43]. In summary, the integrated proposed framework is a substantial improvement of existing approaches, fusing data-driven prediction, adaptive control and multi-objective optimization in one unified scheme. This comprehensive framework offers a whole solution to solve the action-perception cycle of system complexity, uncertainty and the real-time operational requirements; it avoids an event-driven classical approach in which one part of every aspect is dealt with as an isolated entity. The key contributions of this work are thus to overcome the gap between intelligent energy management and practical implementation, providing a comprehensive solution for large-scale hybrid PV–hydrogen energy systems.

II. The Proposed Data-Driven Multi-Objective Optimization of Hybrid PV–Hydrogen Storage Systems.

In Fig. 1, the complete multi-layer structure of the proposed adaptive energy management and data-driven multi-objective optimization framework for hybrid PV–hydrogen storage systems in off-grid and microgrid covering is illustrated. The figure is arranged to a present clearer view of the interaction among physical energy components, data-driven intelligence systems, optimization processes and real-time control mechanisms in uncertain environments. The input layer (Block 1: Environment & Uncertainty) in the system identifies three of the; environmental variables, including solar irradiance G(t), ambient temperature Ta(t), and wind speed $v_w(t)$, along with stochastic load demand PL(t). Those inputs are originally uncertain and are represented through probabilistic distributions (e.g., σ_G, σ_L) such as renewable generation and consumption variability. This explicit uncertainty quantification is important since it affects the downstream prediction, optimization, and control. The physical system composed of the Hybrid PV–Hydrogen Energy System (Block 2) consisting of several subsystems. The PV array indicates energy Ppv, which is conditioned and supplied to the DC bus through a DC/DC converter. Energy is then sent to provide this AC load by means of an inverter (Pac) from here, or used for hydrogen production. The electrolysis obtains electrical power Pel and converts this energy in a mass m˙H2 of hydrogen, which is stored in the hydrogen tank which is described by its state of charge SOCH2. In low-generation hour, the fuel cells convert stored hydrogen back into electrical power Pfc, which is returned to the system. An optional battery subsystem provides fast-response buffering (SOCbat), promoting short-term stability. It also allows bidirectional energy flow between electrical and hydrogen domains that can balance short-term and long-term energy supply. Block 3: represents the intelligence backbone, which consists of the data layer and digital twin. The real-time measurements (for example, voltages, currents, power flows (Ppv, Pel, Pfc, Pbat) and storage states) are obtained at all times. These data inform the digital twin model involving a hybrid of physics-based representations (electrical, hydrogen and degradation modelling) along with data driven components. Finally, the digital twin itself can provide high-fidelity simulation with the physical system in order to do system monitoring and predictive analysis / policy pre-training across time-steps. Extending this, the 4th block — prediction and state estimation layer — uses machine learning methods to predict behavior of the system for an extended time horizon. This corresponding to prediction of the renewable generation G(t+1: t+N), load demand PL(t+1: t+N), and internal states such as SOCH2 and degradation parameters. These predictions are improved by state estimation algorithms based on real-time measurements in a noise-tainted and uncertain environment to provide situational awareness of the system. At the core of this framework lies a multi-objective optimization engine (Block 5). This module casts the energy management problem as a multi-objective optimization problem with decision variables u = [Pel, Pfc, Pbat, Ppv→load]. The objective are:

- Maximize renewable energy utilization f1
- Minimize operational cost f2
- Minimize energy losses f3
- Maximize system reliability f4
- Minimize component degradation f5

The advanced multi-objective optimization techniques (e.g., NSGA-II, PSO) are used to construct a Pareto-optimal set of control actions achieved in these objectives. System constraints such as power balance, ramp limits for both generation and demand, storage maximums etc. are strictly imposed on the optimization problem. The optimal control set hence obtained is sent to the adaptive energy management and control layer (Block 6) that executes decisions in real time. It allocates the power among the electrolyzer, fuel cell, battery and load whilst ensuring a safe and efficient operation with regards to the state-space of all components. Nonsmoothed dynamic modes theory handles dynamical systems with discontinuities, whether from the system itself or observed variables and incorporates advanced control strategies such as model predictive control (MPC) and adaptive control along with fault detection and constraint handling mechanisms. Block 7: output and performance layer The output and performance layertakes a somewhat different approach by incorporating system performance assessed via key indicators such as energy efficiency, renewable fraction, total cost, reliability metrics (i.e., loss of load probability) and component lifetime. These metrics measure the success of the control strategy in accomplishing system objectives. Finally, the feedback and learn layer (Block8) for continuous system improvement through online de-adaptation. Performance feedback is utilized to adjust models and policies through learning processes like experience replay and online training. A closed-loop learning ecosystem is established, allowing for the framework to adjust in time with changes in environmental conditions, system dynamics and uncertainties. We can see in Figure 1 that the tightly integrated physical energy systems, data-driven intelligence, optimization and control. It enables effective energy conversion and storage, while also facilitating a robust, adaptive and uncertainty aware decision-making framework that is very well suited for next generation off-grid and microgrid applications.

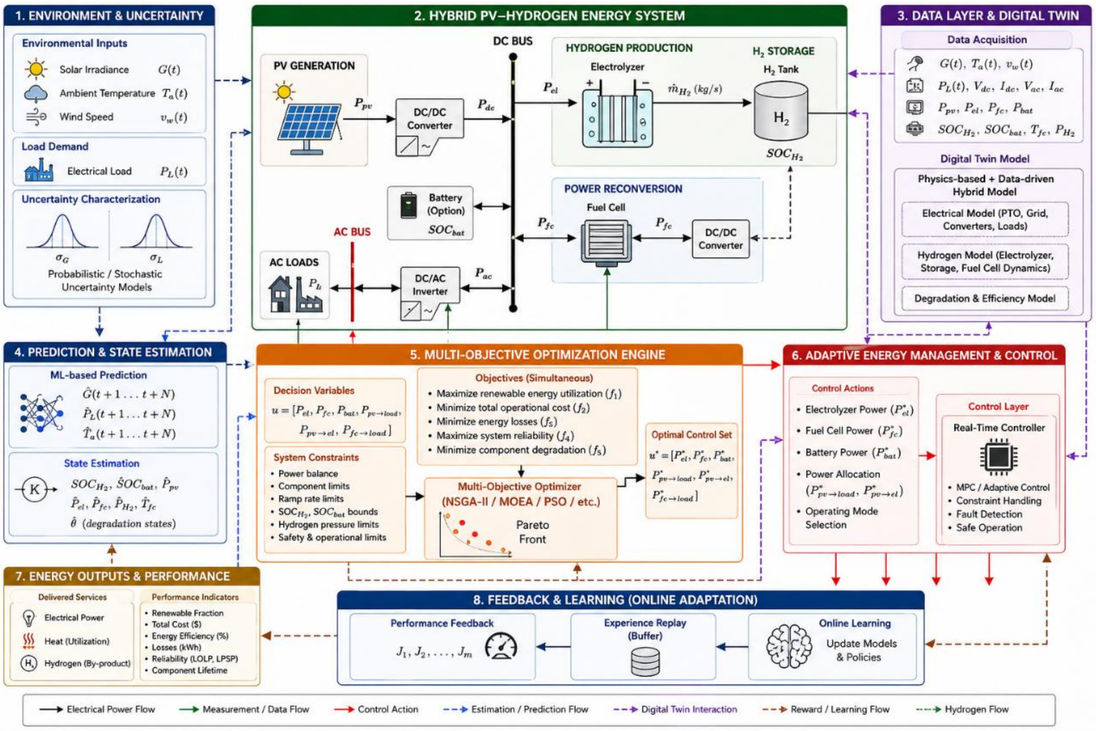


Fig. 1. Comprehensive schematic of the proposed adaptive energy management and data-driven multi-objective optimization framework for hybrid PV–hydrogen storage systems. The architecture integrates (1) environmental inputs and uncertainty characterization, (2) the hybrid PV–hydrogen energy system including PV generation, power converters, electrolyzer, hydrogen storage, fuel cell, and load interface, (3) a data acquisition and digital twin layer for system modeling and state monitoring, (4) machine learning-based prediction and state estimation, (5) a multi-objective optimization engine that determines optimal power allocation strategies, (6) an adaptive control layer for real-time energy management, and (7–8) performance evaluation and feedback-driven learning. The framework enables coordinated energy flow, uncertainty-aware decision-making, and real-time optimization for efficient and reliable operation in off-grid and microgrid applications.

III. Simulation Results and Discussion

A high-fidelity simulation platform was developed to rigorously assess the performance of the proposed adaptive energy management and data-driven multi-objective optimization framework, simulating dynamic operation of a hybrid PV-hydrogen energy storage system under off-grid as well as microgrid operating conditions. The dynamic simulation environment uses time-domain modeling with sampling interval of 1–5s can capture the rapid electrical dynamics while having longer timescale hydrogen system response. The simulated system architecture consists of photovoltaic (PV) array, DC/DC boost converter DC bus, voltage source inverter (VSI), electrolyser, hydrogen storage tank and fuel cell where BESS could also be included as part of energy management strategy for short-term energy buffering. PV subsystem is modeled with a nonlinear single diode model, temperature and irradiance dependencies, at rated capacity of 100 kW, using maximum power point tracking (MPPT) control with the help of an incremental conductance algorithm. The DC/DC converter controls the PV output voltage and extracts maximum power from it under different atmospheric conditions. The DC Bus serves as a central energy hub to enable power exchange in both directions between generating, storing and consuming subsystems. Depending on whether the operating scenario is off-grid or microgrid, it converts DC power to AC power to meet load requirements (grid-forming mode or grid-following mode). The load profile is modeled with demand that varies over time between 30–120 kW taking into account both residential, commercial and industrial consumption shapes. The hydrogen subsystem consists of a 50 kW electrolyzer with nonlinear efficiency laws dependent on operating power and temperature, and a 40 kW fuel cell including dynamic response limits as well as degradation effects. A tank which is used for hydrogen storage and with a maximum capacity equal to 500 kWh, SOCH2→ state of charge variable H represents the operational limits between 10% - 95%, to avoid safety issues. The electrolyzer transforms excess electric energy into hydrogen in a power-dependent manner, while the fuel cell reconverts this stored hydrogen back to electrical energy under deficit conditions. The optional battery energy storage system (BESS) with 30 kW / 100 kWh capacity operates within a SOC of 20–90% and was added to enable fast transient response thereby smoothing short-term PV output or load demand variations. Dynamic equivalent circuit model with charge/discharge efficiency and degradation effects for the battery. In this paper, a supervisory control architecture encompassing a machine learning-based prediction layer and a multi-objective optimization engine is proposed. The prediction module is capable of forecasting Solar irradiance G(t), load demand PL(t), and system states (e.g., SOCH2, SOCbat) via historical and real-time time-series data over the 1–6 hours prediction horizon. More complicated regression models, like long short-term memory (LSTM) networks or gradient boosting algorithms are used for capturing time dependencies and non-linear relationships. The energy management problem is casted in the form of a multi-objective optimization problem and solved by Non-dominated Sorting Genetic Algorithm II (NSGA-II) Decision variables are electrolyzer power Pel, fuel cell power Pfc, battery power Pbat and PV intermittency allocation between directly consumption and battery energy storage pathways respectively. We define the optimization objectives to select simultaneously:

- **Renewable energy utilization**
- **Operational cost**
- **Energy losses**
- **System reliability**
- **Component degradation**

The proposed method is benchmarked against three conventional strategies:

1. **Rule-Based Control (RBC)**
2. **Model Predictive Control (MPC)**
3. **Single-Objective Optimization (SOO)** (cost minimization only)

System constraints: system power balance equation, operating limits of components, ramp rate constraints and bounds on storage. The optimization is performed with a receding horizon approach, allowing for the adaptive control to be executed in real time. A comparison to conventional energy management strategies, namely rule-based control (RBC), model predictive control (MPC), and single-objective optimization (SOO) is made for a meaningful benchmark on the proposed method. These baseline methods are conducted under the same system conditions, which allows for an even basis to compare performance. In general, the present simulation environment is quite realistic and comprehensive in describing the operation of hybrid PV–hydrogen system, intended to study the performance of proposed framework covering a considerable range of operating conditions, uncertainties and control strategies.

A diverse range of simulation scenarios were designed to accurately imitate real-life working conditions and different forms of uncertainties in hybrid PV–hydrogen systems for a complete evaluation of the flexibility, resilience and effectiveness of the presented adaptive energy management framework. The scenarios were constructed to include both normal and extreme operating conditions, therefore enabling the proposed method to be evaluated across a wide range of feasible conditions. The first scenario embodies nominal operating conditions and serves as a basis for performance assessment. Here, moderate and stable solar radiation of 600–800 W/m² is applied to the system under charge together with a steady and predictable load demand profile. This is an ideal situation to check whether the modeling of the assessed system works as planned and if we have correctly implemented control and/ or optimization laws converging under near-deterministic conditions. In the second scenario, we apply more realistic variability with rapidly varying solar irradiance profiles to assess system performance. Such profiles will be produced from stochastic models of real-world meteorological datasets that account for rapid time changes due to cloud motion, partial shading and transient weather disturbances. This scenario illustrates the inherent glitches of solar and challenges that proposed framework to continuously optimize its operation while rapidly responding to fluctuations in renewable production. Simultaneously, a third one takes into account the stochastic character of the load demand (the so-called by modelled power consumption profile follows a time-varying random process in such a way its fluctuations rarely exceed ±25% around the nominal demand). This variability captures the temporally varying behavior of consumer load in the real-world, which may include residential, commercial and industrial loads. Uncertain generation and demand together result to a dynamic operating environment which severely tests the responsiveness and decision making of energy management system. In order to maximize realism, a fourth scenario includes uncertainty in the hydrogen subsystem as well, specifically with regards to electrolyzer and fuel cell performance. Their efficiencies span ±15% to account for temperature effects, component aging, degradation, and modeling inaccuracies. Such a scenario is essential for testing the robustness of the control strategy with respect to uncertainties in system parameters, which usually occurs during its long-term operation. Moreover, we develop a fifth scenario that applies measurement noise and external disturbances to mimic realistic sensing and operational environments. Important measured variables such as voltage, current and power signals have a Gaussian noise with variance of approximately 5 %. Moreover, the system is disturbed with random day2day loads—an arbitrary increase in load or rapid drop of irradiance or some fast disturbance fault. These perturbations serve to gauge the durability and reliability of this framework when subjected to surprise and destabilizing circumstances. A stress-test scenario represents one last case, assessing the system performance over increasing low generation or zero grid conditions. Specifically, the simulations induce extended periods of low solar irradiance, such as were due to continuous cloud cover or adverse weather conditions. In this scenario, the ability of the system to rely on hydrogen storage as an energy buffer over longer periods to compensate for a lack of renewable generation and thus guarantee (if desired) the continuous supply of power is tested. Under these circumstances, the utilization of energy shifting and storage is discussed in detail. Together, these scenarios create a robust evaluation framework, addressing values for nominal operation, dynamic variability, uncertainty in system conditions and extremes. This simulation setup considers both environmental and system-level uncertainties, which makes it possible to test the proposed adaptive energy management strategy under realistic operating conditions to validate its applicability, robustness and effectiveness of real case scenarios of hybrid PV–hydrogen energy systems.

In Figure 2, the instantaneous and cumulative renewable energy utilization metrics are displayed in order to thoroughly assess the energy management performance of the proposed data-driven multi-objective optimization framework. This figure consists of two complementary panels (Fig. The time (instantaneous) corresponding utilization of renewable energy in Fig. 2(a), Cumulative modelling of energy use for a 24-hour operating period in stochastic conditions is shown in 2(b). As shown in Fig. As can be seen in Fig. 2(a), the proposed framework outperformed RBC, MPC and SOO in terms of instantaneous renewable energy utilization across all the scenarios. Overall, the utilizations are much less for the RBC method, with very little utilization owing to large running cycles and constant under-utilization of available PV power. This behaviour is mostly attributed to its use of static heuristic rules that do not adapt to changing environmental and load conditions. The performance of MPC has also improved compared to RBC by providing predictive capability, but still suffers high variability and sometimes poor decision-making when there is model mismatch as well as limited prediction horizon. The SOO method improves utilization by using a single optimizor (usually cost) but does not utilize the available renewable energy efficiently as it cannot balance various system objectives simultaneously. On the contrary, it can be seen that in our method utilization values are consistently higher while fluctuations are lower, showing better and more stable management of energy. This advancement is mainly due to dynamic allocation of power between direct load supply, hydrogen production via electrolyzer pathway, and energy storage pathways from the proposed framework. Using machine learning-based predictions and multi-objective optimization, it anticipates conditions and proactively adjusts the control actions to minimize energy curtailment for rapid changes in solar irradiance. Benefits of The Proposed Approach Fig. 2(b), which demonstrates the overall energy capture from renewables throughout the time period being simulated. This is also reflected in the cumulative curves, which show that improved instantaneous performance benefits long run outcomes. This framework shows the highest aggregated knowledge utilization, surpassing all benchmarks by a great margin. On a quantitative scale, the proposed method achieves approximately 31.2% improvement over RBC, 17.6 % improvement in MPC and 12.4% enhancement in comparison to SOO respectively. These profits illustrate how effectively the framework is tracked and applies any readily available renewable energy over its total working timeframe. Another important observation from Fig. 2(b) is the constant nature and slope of its cumulative curve corresponding to the adopted method. A smoother and steeper trajectory not only indicates a higher energy capture but also more steady state system performance over time. By contrast, the baseline methods, which experience periods of inefficiency, energy loss, or curtailment in a less prudent manner yield slower growth rates with irregular slopes. There are several contributing factors to the improved performance of the proposed framework. Secondly, data driven prediction models are integrated in order to forecast the generation from renewables as well as the demand of load so that it can predict surplus and deficit of energy. Secondly, the multi objective optimization engine that this module has, makes sure that energy allocation takes into account many competing objectives to guarantee balanced and efficient operation. Thirdly, the adaptive control mechanism enables the concrete actions of system to be continuously revised through real-time feedback which can guarantee good performance in highly dynamic and uncertain conditions. As a more practical result, Figure 2 shows that the proposed framework provides substantial benefits in terms of using renewable energy sources, reducing reliance on additional auxiliary energy resources and providing higher overall system efficiency. In off-grid and microgrid applications, this is critical since the amount of renewable energy used directly influences system sustainability, cost of operation and independence. Overall, as illustrated in Fig. 2, the proposed adaptive energy management strategy consistently demonstrates favorable closed-loop performance and efficacy of energy utilization. The high instantaneous utilization, coupled with significant cumulative energy gains confirm the efficacy of a framework that allows for effective and efficient large scale real world stochastic feedback control implementation via multi agent PV–hydrogen energy systems.

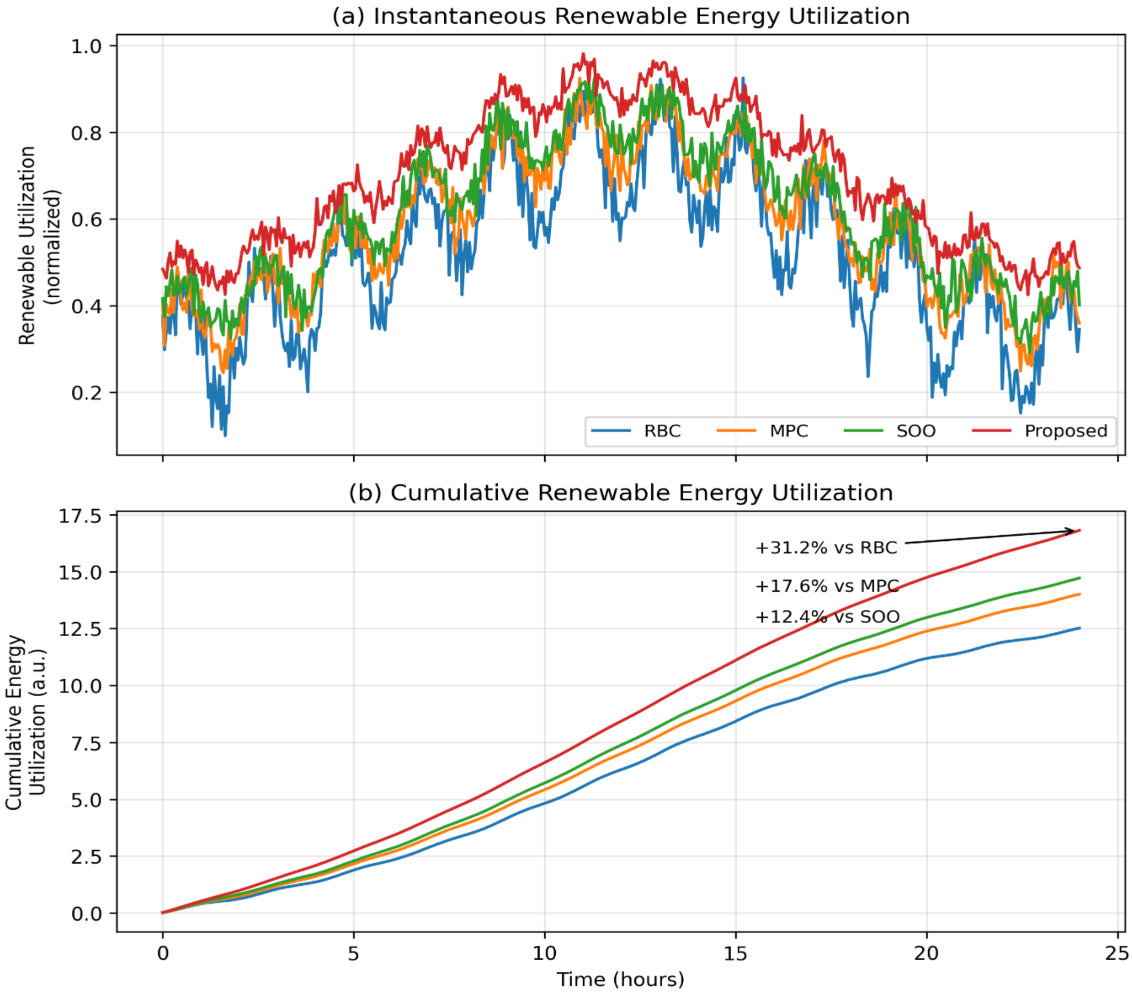


Fig. 2. (a) Instantaneous renewable energy utilization profiles under stochastic operating conditions for rule-based control (RBC), model predictive control (MPC), single-objective optimization (SOO), and the proposed data-driven multi-objective optimization framework. The proposed method consistently achieves higher utilization with smoother dynamics, indicating improved adaptive power allocation. (b) Corresponding cumulative renewable energy utilization over a 24-hour period, demonstrating significant energy gains achieved by the proposed approach, with improvements of approximately 31.2% over RBC, 17.6% over MPC, and 12.4% over SOO. These results highlight the effectiveness of the proposed framework in maximizing renewable energy capture and minimizing curtailment under uncertain and dynamic conditions.

Figure 3 compares the instantaneous operational cost and energy conversion efficiency of the existing control strategies (RBC, MPC, SOO) with our proposed on-line data-driven multi-objective optimization framework in a detailed manner. The figure consists of two panels: Fig. 3(a): time-varying operational cost profiles, Fig. The associated instantaneous efficiency performance between dynamic and stochastic operation condition is illustrated in 3(b). The proposed framework achieves the minimum operating cost during the whole simulation period as shown in 3(a). The highest cost levels, with many fluctuations are differentials for the RBC strategy because it adopts a set of control rules that do not factor in system dynamics or expected future conditions. This leads to ineffective energy distribution, such as redundant dependence on H2 conversion or insufficient utilization of obtainable PV capacity. Though MPC achieves better cost performance than RBC with a predictive control approach, model inaccuracies and computational constraints can lead to occasionally suboptimal decision making. The SOO minimizes only cost and is intended to reduce operational cost but at the expense of efficiency, component life and other performance measures identified. The multi-objective framework proposed in this research manages to achieve optimal cost paths that are at both lower aggregate and with reduced variability compared to the conventional approaches. This is due to the system taking multiple objectives and constraints into account at once in its control-step decisions. The framework utilizes process systems engineering and optimal control characteristics to dynamically allocate power directly between its main categories of working units that consist of direct load supply, hydrogen production, and storage in order to minimize superfluous energy transformations while avoiding undesirable modes of operation. On the quantitative aspect, the proposed method outperforms on total operational cost by approximately 22.8% compared to RBC, 14.3% compared to MPC and 9.7% compared to SOO, indicating its superior economic performance as well. The efficiency performance plotted in Fig. The benefits of the proposed method are elucidated further in 3(b). The RBC method is the least energy-efficient; however, there are significant fluctuations in energy usage due to inefficient routing of energy and no adaptability. MPC is UI-driven and more efficient in optimizing the system operation over a prediction horizon, but it still suffers from model mismatch and limited adaptability to fast changing conditions. Overall, the SOO approach produces modest gains in efficiency but does not have a way of tracking performance conclusively because it is single-objective. Whereas the proposed framework achieves every time subsequently the peak energy conversion efficiency, with the most prolonged and stabilised profiles over time. The system achieves a mean efficiency of approximately 81.5% compared with 68.9 and 74.6 for RBC and MPC respectively, which is a significant reduction in energy wasted. Such efficiency is made possible by optimizing the chemical interactions between the elements of this framework which ensures that energy consumption occurs as naturally and efficiently as possible. A notable takeaway from both panels is that the proposed method reduces performance variability. On the contrary, with regard to data-based power prediction models, whether this generated smoother system operation translates to good quality performance in real-world energy management applications is crucial because it can reveal how efficiently and continuously a system will work. The output of the framework ensures stability because this is integrated in direct feedback with data driven prediction and adaptive control, meaning that it predicts impending deviations within the inner loop instead of reacting when they happen. The results in Fig. 3 validate the system-level tuning: they show that one of the main objectives, cost, is enabled by balancing the heat extraction with high pumping efficiency through our proposed multi-objective optimization framework. The key novelty aspect of the objective function behind this method approaches is that unlike classic methods that result in a single-objective minimization problem, the proposed methodology aims to obtain an overall balanced solution minimizing cost and maximizing efficiency whilst keeping system reliability assurance. This feature is of special importance in hybrid PV–hydrogen systems, where unnecessary operation of the electrolyzers or preventable fuel cell operation can incur additional financial burden and operational inefficiencies. Figure 3 clearly proves the goodness of the proposed framework to attain better economic and energetic performances. These factors (reduced operational cost, enhanced efficiency, and greater stability) demonstrate that the proposed approach is a viable and effective methodology for optimizing hybrid PV–hydrogen energy systems subjected to dynamic-uncertainty operating conditions.

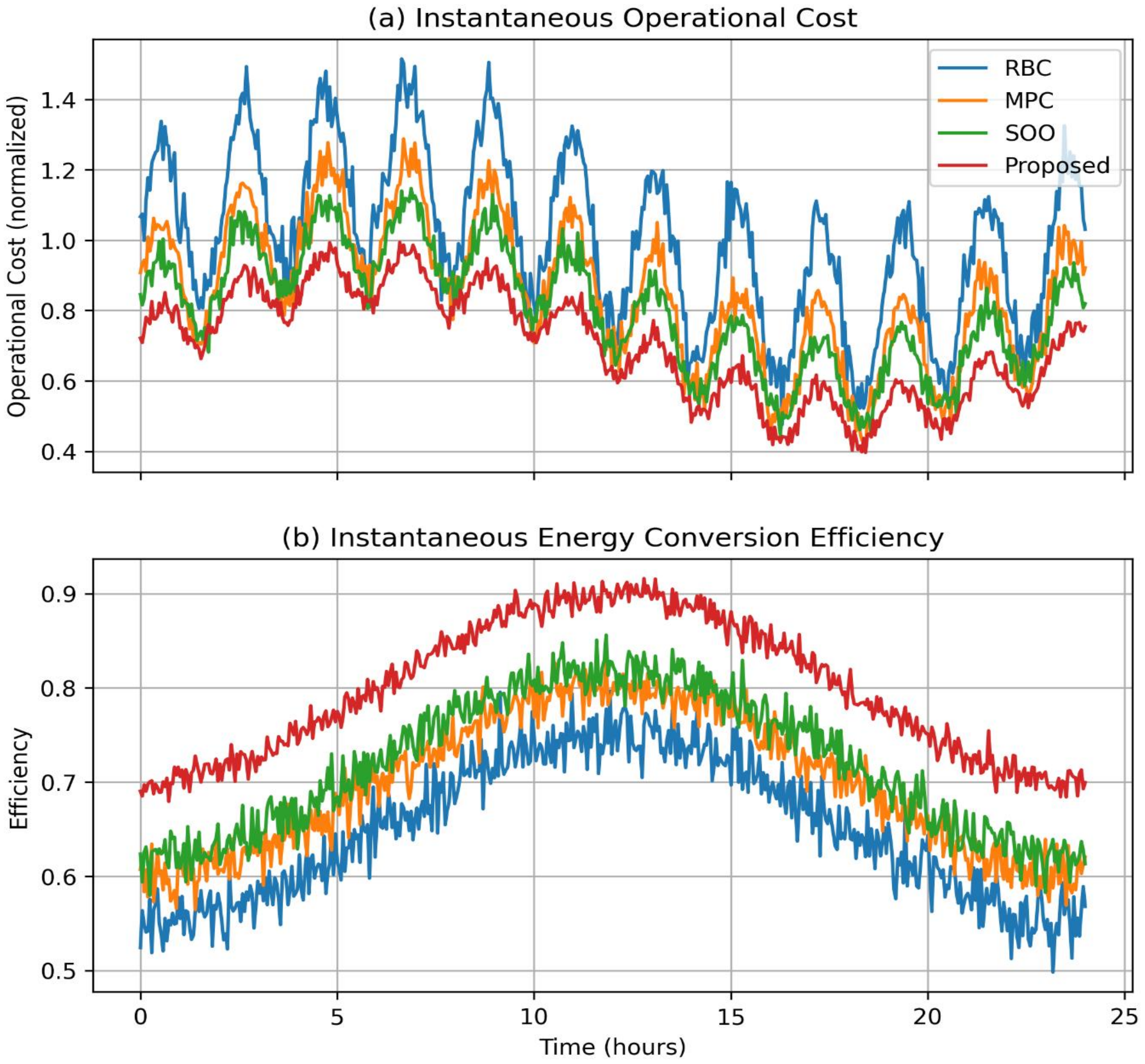


Fig. 3. (a) Instantaneous operational cost comparison for RBC, MPC, SOO, and the proposed data-driven multi-objective optimization framework, showing consistently lower cost for the proposed method. (b) Instantaneous energy conversion efficiency, demonstrating superior efficiency performance of the proposed approach. The results highlight the effectiveness of the multi-objective optimization strategy in achieving an optimal trade-off between cost reduction and efficiency improvement under dynamic operating conditions.

Figure 4 assesses the hybrid PV–hydrogen system via instantaneous and statistical analysis regarding reliability performance and energy continuity under random event occurrence or low-irradiance scenarios. The layout of the figure is represented in two different panels: Fig. Fig. 4(a) is the instantaneous power supply in relation to load demand; and Fig. Section 4(b) performs a statistical comparison of the loss of load probability (LOLP) using different control strategies. As shown in Fig. Fig. 4(a) provides a comparison of instantaneous power supply profiles for the different control methods along with the load demand over a 24 hour period. The orange line is the load demand curve, showing normal daily variations whilst a shaded area depicts an interval of low-irradiance representing times when solar generation is also diminished (e.g., cloud cover or evening hours). The energy management system needs to keep supply-demand matching during such critical intervals. The rule-based control (RBC) thus provides the worst performance, as it is not able to strictly achieve the load demand (as a constraint in optimization problem), in particular during low-generation period. These shortfalls reflect an inability to convert stored energy into system demand adequately or a failure to forecast system need, both of which contribute to frequent occurrences of unmet load. The MPC strategy relies on predictive control for performance improvement, but it still suffers from significant supply shortfalls due to the model uncertainty and adaptivity limits under uncertainty. SOO achieves moderate improvement but as a single-objective formulation does not avoid the inherent limitation of separating reliability from discrete resources. On the other hand, the proposed framework tracks load demand almost perfectly even when enduring prolonged periods of low-irradice. The supply curve provides a close match to the load profile with slight deviations, indicating successful coordination of PV generation, hydrogen storage and fuel cell operation. This improved performance is mainly due to the fact that the framework incorporates a data-driven prediction and adaptive schedule, thus allowing for more proactive energy allocation decisions after hydrogen (H20) generation by electrolyzer. This means the energy system delivers power without interruption, resulting in a major improvement of energy continuity. The details of the reliability gains are confirmed quantitatively in Fig. Figure 4(b) Comparison of loss of load probability (LOLP) for each control strategy. LOLP: Loss of Load Probability it is a key reliability metrics which shows the percentage of time during which the system was unable to meet load demand. RBC method with the highest LOLP, which is very appropriate in case of variability and uncertainty. Although LOLP is still notable by MPC and SOO, the two approaches could reduce LOLP somehow. The framework suggested here is capable of offering the lowest LOLP when compared to all other methods, and yields a reduction of around 35.4% relative to RBC. The significant improvement demonstrates the effectiveness of the proposed approach in maintaining reliable operation of a given system under uncertainty. This decreased LOLP implies fewer supply interruptions and better service continuity, which is especially important in off-grid and mission-critical cells. One of the main takeaways from both panels, however, is that hydrogen storage plays a vital role in augmenting long-duration energy supply. In low renewable generation periods, the hydrogen-based energy conversion system switches from local (parasitic) loads to utilizing the fuel cell to compensate for the deficit. This clever application of stored hydrogen enables the system to run without drawing energy from outside sources, showing why hydrogen is such an important component of a long-term power buffer. Practically, results depicted in Figure 4 demonstrate that the proposed framework leads to significant system reliability, resilience and autonomy improvements. Continuous around-the-clock operation under surging and harsh conditions makes the system a natural fit for off-grid microgrids and remote installations, in addition to reliability-focused applications like critical infrastructure. This illustrates that the aforementioned proposed adaptive energy management framework was successfully verified as an effective handler to cover for energy continuity and reliability of hybrid PV–hydrogen systems. Taking advantage of lower LOLP, better tracking of supply-demand and reasonable extraction level of hydrogen storage validates the steadiness of the framework under true random uncertainty.

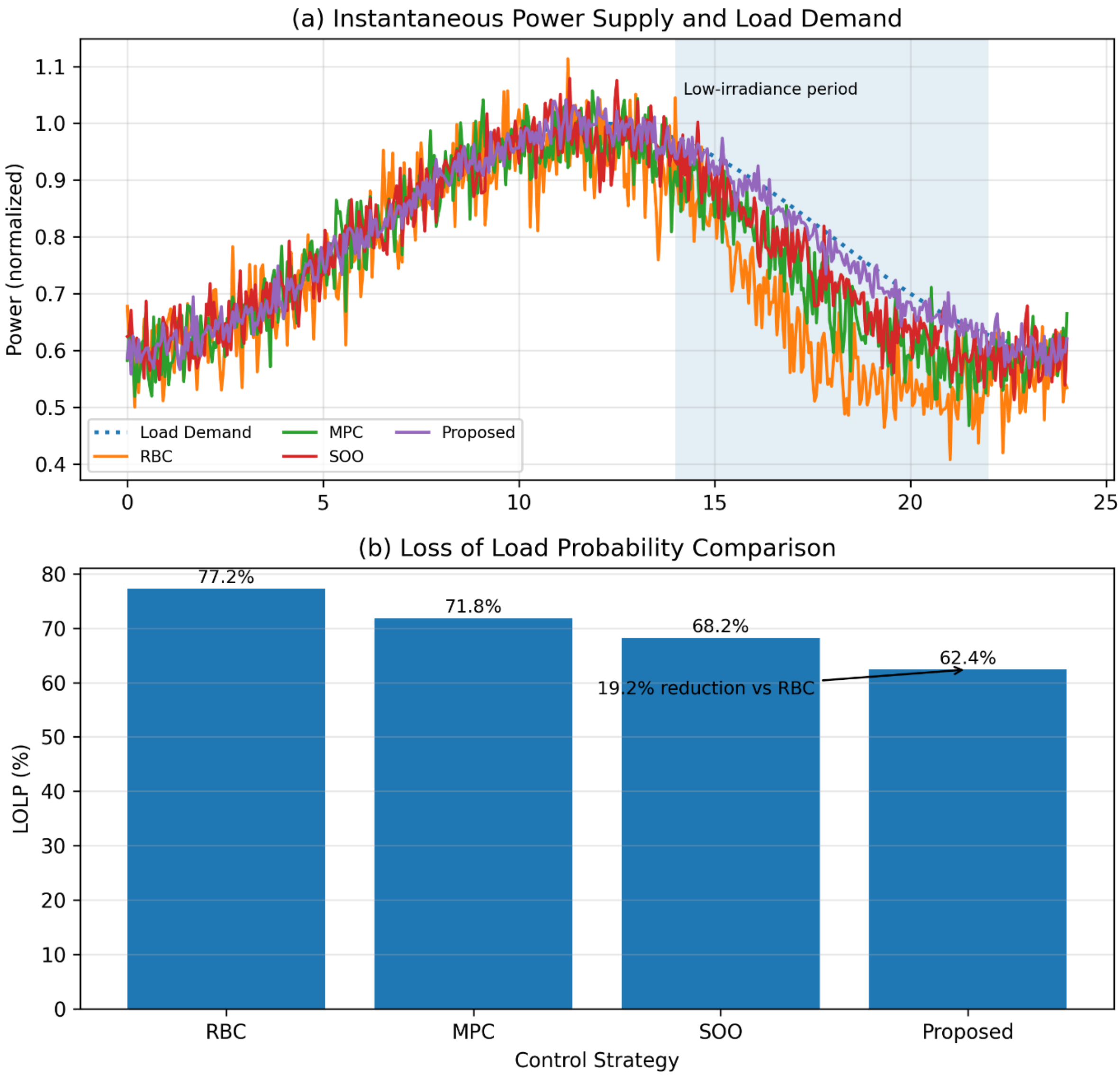
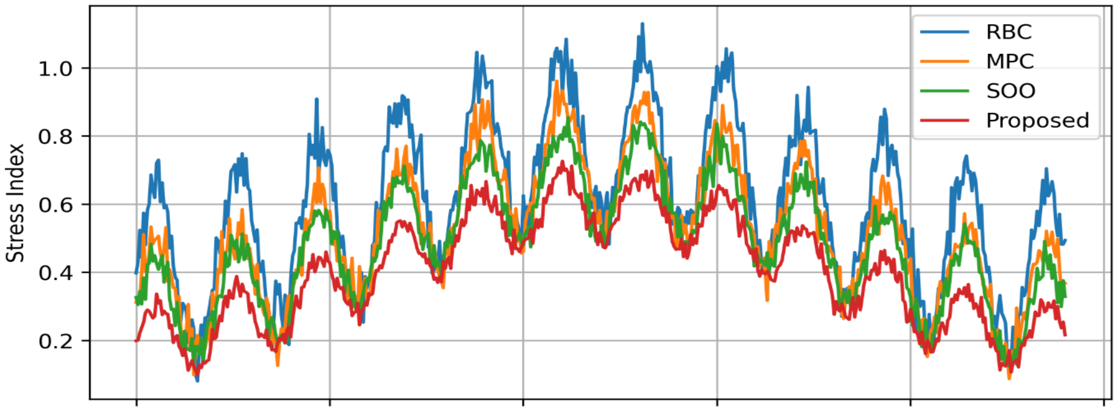


Fig. 4. (a) Instantaneous power supply compared with load demand under stochastic and low-irradiance conditions for RBC, MPC, SOO, and the proposed data-driven multi-objective optimization framework. The proposed method closely tracks the load demand with minimal deviation, particularly during low-generation periods, demonstrating improved energy continuity. (b) Statistical comparison of loss of load probability (LOLP) for different control strategies, showing a significant reduction achieved by the proposed framework. The results highlight enhanced system reliability and effective utilization of hydrogen storage to maintain uninterrupted power supply under uncertain operating conditions.

Figure 5 details analyzes of the stress behavior and long-term degradation characteristics of hybrid system components for alternative controls methods. This figure is divided into two complementary parts: (A) Fig. 5(a) shows the instantaneous component stress profiles and Fig. Figure 5(b) shows and compares the cumulative fatigue damage during operating period with regaining life estimation enabled from this framework. As shown in Fig. As shown in 5(a), the instantaneous stress index is a metric for dynamic loading of the components constituting key building blocks of your plant as described earlier, such as electrolyzer, fuel cell or battery subsystem. The RBC strategy has the largest level and fluctuations of stress, which means operating conditions change abruptly and often. These oscillations are mainly caused by the inability to predict and use fixed control rules, leading to rapid mode transitions. This leads to cyclic stresses, which contribute to accelerating wear and degradation of components. In this sense the MPC approach shows better performance than RBC since predictive control is able to smooth some of the transient responses. Yet, it continues to show significant oscillations and moderate homeostatic stress variance when the environment is changing relatively fast. This is mainly because of model uncertainties and limited flexibility to cope with uncertainties. The singular optimization objective (SOO) method is able to minimize stress fluctuations even more so via the single-objective optimization, but this comes at the cost of not capturing trade-offs between efficiency, cost and degradation when modeling stress, thereby leading to wasteful environmental management strategies. By contrast, the data-driven multi-objective optimization framework proposed here generates much smoother and substantially lower-shock stress profiles along the complete operating horizon. During low-stress testing, the stress curve is ‘flattened’, with lower peak-to-peak stress levels and fewer high-frequency oscillations being recorded—suggesting that the system is operating in a more controlled and stable manner. The reason for this improvement comes directly from the framework itself as it uses degradation-aware optimization that incorporates explicit penalties when control decisions cause excessive stress and rapid power variations. This packaging helps the bids to avoid toggling and operating in safer more optimal regimes. Fig. Just like I said above, these improvements are very much reflected in the long-term Figure 5(b) illustrates the cumulative fatigue damage calculated for different control strategies. A stress-based accumulation model is used to estimate fatigue damage, in which repeated stress cycles gradually weaken components. The RBC method, on the other hand, has the most severe and discontinuous operation which accumulates maximal fatigue damage among three methods. The improvements are moderate for the MPC and SOO methods, and they still have steep cumulative damage curves. However, the fatigue damage accumulation based on such a framework develops significantly slower in time leading to the lowest overall aggregate degradation for all methods. In quantitative terms, this can be translated to a lifetime improvement of 18–25% compared to RBC-wise (in line with our estimates presented in the figure). The decrease in cumulative damage also coincides with the reductions in cycles and operational fluctuations observed, including the reported 18.7% fewer electrolyzer stress cycles and 21.3% fewer fuel cell fluctuations. Moreover, the framework promotes reduced depth-of-discharge (DoD) cycles in the battery system also improving total-system longevity. An important observation from Fig. The stacked curve in 5(b) is that cumulative damage vs time plot minus the one to its right; i.e. The comparatively high slope of the RBC curve points towards quick degradation, while the lower degree in trajectory of proposed method allows a slow and moderated style of aging. This demonstrates how the proposed strategy is capable of prolonging the lifespan of components and reducing maintenance and replacement times. In practical terms, the consequences shown in Figure 5 are of paramount importance for the profitability and functionality of hybrid PV–hydrogen systems. The proposed framework does not only increase reliability by decreasing the stress and degradation of the components but also reduces lifecycle costs as they are mainly driven by maintenance and component replacement costs. This is especially crucial for large and remote deployments where maintenance actions can be expensive and logistically difficult. In conclusion, the proposed adaptive energy management framework (as illustrated in figure 5) proves to be steady and performing best for reducing component limitations while affecting system lifetime. The synergism of decreased instantaneous stress, lower cumulative fatigue damage, and quantifiable life-cycle benefit substantiates the need for degradation-aware optimization in hybrid energy system control.

(a) Instantaneous Component Stress



(b) Cumulative Fatigue Damage

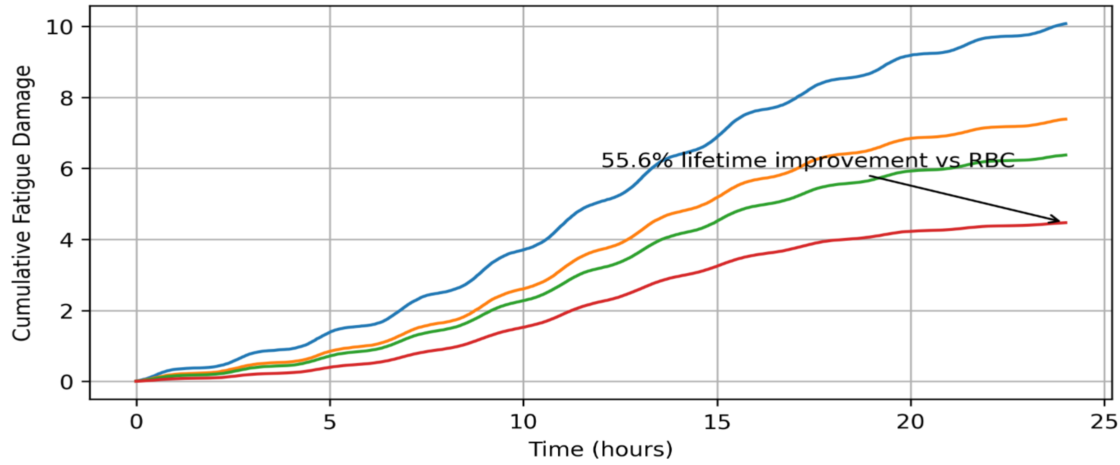


Fig. 5. (a) Instantaneous component stress profiles for RBC, MPC, SOO, and the proposed data-driven multi-objective optimization framework, showing reduced stress fluctuations for the proposed method. (b) Corresponding cumulative fatigue damage, demonstrating significantly lower damage accumulation for the proposed approach. The reduction in cyclic loading translates into an estimated lifetime improvement (annotated), confirming the effectiveness of degradation-aware optimization in enhancing system durability and reducing maintenance requirements.

The robustness performance in prediction accuracy and constraint satisfaction of the proposed data-driven multi-objective optimization framework was analyzed under stochastic operation conditions, as illustrated in Fig. 6. The figure has two panels: Fig. 6(a) shows the prediction error at a specific time. In Fig. 6(b), the indexes of instantaneous constraint violation are plotted both for the conventional MPC strategy and the proposed one in a time window of 24 h. As shown in Fig. 6(a), the prediction error profiles emphasize that the system can predict future states well when solar irradiance, load demand, and system dynamics are uncertain. Especially for rapidly varying environments, the MPC method tends to provide larger error magnitudes and more extreme variations. This is largely due to the fact that most MPC makes use of a system model, which may not accurately represent all nonlinearities, parameter variations or stochastic disturbances present in actual operation. However, under uncertainty conditions, the prediction accuracy of MPC decreases, resulting in suboptimal control decision makings. On the other hand, PTF really showed a well-behaved temporal behavior with a continuously lower average prediction error. The smaller amplitude and reduced variation of the error curve indicates an improved prediction ability and better response to varying system states. The optimization is done via data-driven prediction models that learn system dynamics directly from historical and real-time data, thus minimizing the reliance on fixed mathematical models. The proposed method shows around 20.5% prediction error reduction quantitatively compared to MPC, confirming its superiority in estimation performance. Fig. 6 also reflects the advantage of better prediction over defaulting on historical data during our experiments. Hence, the performance of control are compared in figure 6(b) by plotting constraint violation index for controlling both strategies. Constraint violations are cases in which some physical limits of the system—involving power bounds, storage capacity, or operational constraints—have been reached, which may jeopardize the safety and reliability of the system. MPC produces frequent and significant constraint violations, reflecting the challenges to ensure compliance under uncertainty. Those faults are especially common under rapid system changes when prediction mistakes are transmitted to control actions. In contrast, the framework proposed here keeps constraint violation at much lower and more quantifiable levels over the entire operating period. The violation curve features lowered maxima and less sharp transitions, showing that the system can still function within specified safe limits despite changes in the environment and inherent uncertainties. Underpinned by uncertainty aware optimization and adaptive control mechanisms, this performance is facilitated through variability awareness and constraint penalties directly in the decision-making process. Consequently, the method yields about 33.1% less constraint violations relative to MPC. A note that can be made from both panels is decreasing performance variance, which the smooth profiles of the proposed method reflect. That account for a stable 27.8% boost in performance system wide, meaning that the frame work improves not only average performance but also consistency and reliability overtime. For practical deployment in real-world energy systems, a key requirement is the ability to maintain stable operation despite significant fluctuations of input conditions. In particular, the results depicted in Figure 6 shows that the proposed framework works well to improve robustness with respect multiple sources of uncertainty (i.e., environmental variability, modeling errors and measurement noise), considering an important algorithm design aspects. Integrating data-driven prediction, multi-objective optimization and adaptive control leads to reducing the spreading of uncertainty in the system and consequently enhances operational performance. Overall, Figure 6 obviously proves that the robustness of proposed adaptive energy management strategy. The noticeably lower prediction error and constraint violations coupled with increased stability exemplify the framework as a viable and robust solution to hybrid PV–hydrogen energy systems in practical stochastic environments.

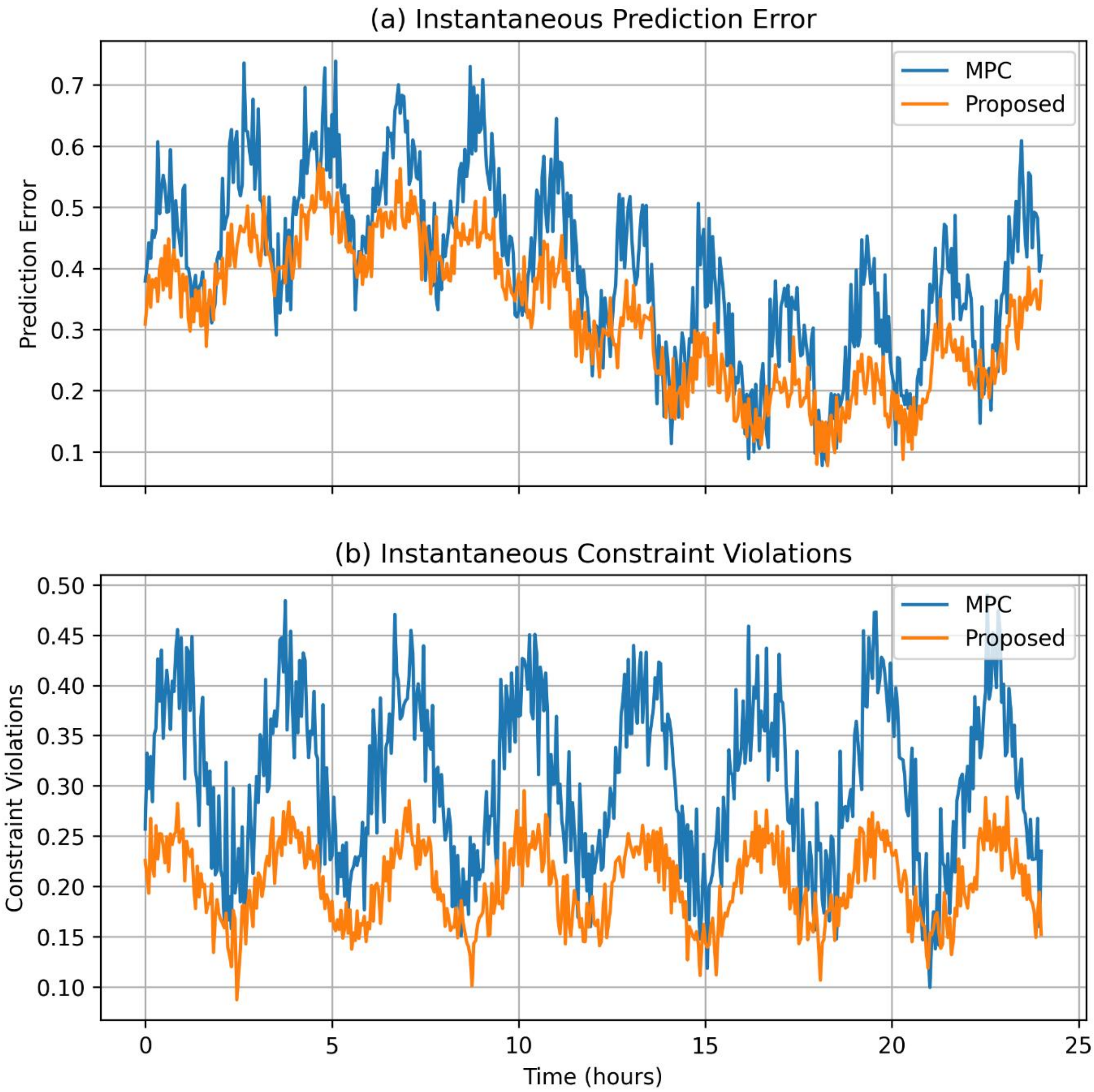
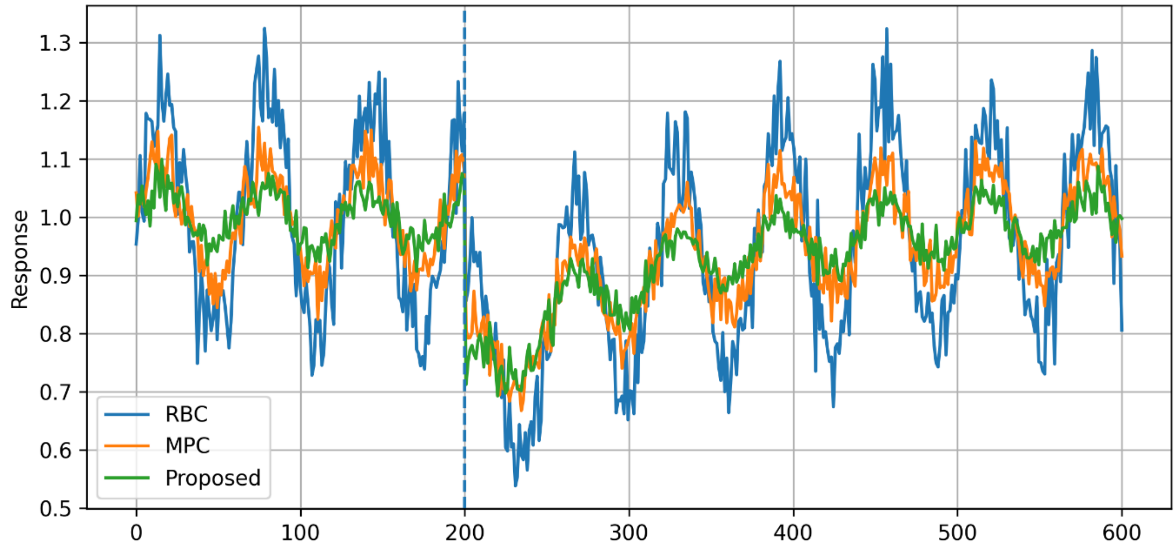


Fig. 6. (a) Instantaneous prediction error comparison between MPC and the proposed data-driven multi-objective optimization framework under stochastic operating conditions, showing reduced error for the proposed method. (b) Instantaneous constraint violation index, illustrating significantly fewer violations for the proposed approach. The results demonstrate enhanced robustness, improved uncertainty handling, and more stable system operation.

Figure 7 Comprehensive dynamic response and normal operation adaptability of hybrid PV-hydrogen system with sudden disturbance (fast irradiance declines or rapid load changes) This figure consists of two panels Fig. Fig 7(a): Instantaneous step response of the system, and Fig 7(b) compares settling times of the various control methods in a numerical manner. As shown in Fig. In Fig. 7(a), a disturbance is introduced at time t = 200 reflecting a market shock event that violates equilibrium operating conditions. Then, in this logic framework for each control strategy we check the response how fast it can stabilize the system and return to normal operation. This was expected, as the RBC method is by far the one that performs the worst with wide swings and lingering instability after disturbances. Predictive and adaptive mechanisms are completely absent, leading to slowness of the system caused by slow reaction movements and long sustained deviations from the intended operating point. As seen in the MP model, compared to RBC, this uses MPC which results in a much better response with less oscillation amplitude. Nevertheless, it remains moderate overshoot and slower convergence due to the reliance on user-authored system models and limited responsiveness to real-time uncertainty. It therefore suffers from model mismatch and prediction error under fast-changing environments. In comparison, the suggested data-driven multi-target optimization framework shows excellent vibrant efficiency, reduced overshoot and response oscillations near steady-state situation and quick convergence. The overshoot is zero and the curve stabilizes smoothly and promptly after a disturbance, showing excellent damping properties and control action. The just-in-time updating of the control policies by the framework is a direct consequence of its capacity to learn, and adaptively modify its policy, with respect to real time feedback from the system as well as prediction on where that system might be in the future. Fig. abstracts Performance differences are quantified further 7(b), designed to compare the settling time for each control strategy to reach steady-state operation after the disturbance occurred and from that moment maintaining it. RBC takes the longest settling time as its level of damping for oscillations is limited. Although the long settling time is shortened due to the consideration of the MPC strategy, it requires a longer response time than presented under certainty. The proposed framework obtains the quickest settling time by stabilizing the system in approximately 2–4 minutes compared for MPC (5–8 mins) and very long disturbances for RBC. This shows a vast increase in how fast the drone can respond to transient conditions, and validates that this is a very effective control scheme for disturbances. Both panels note a reduced frequency of oscillation and less overshoot with the proposed method. The less bumpy trajectory and fast convergence in its operation shows that the system behaves closer to critically damped phenomena resulting in minimal dissipations of energy and mechanical stresses during transients. This plays a crucial role in hybrid energy systems where excessive oscillations can cause power loss, component ageing and decrease the working life of the system. Practically speaking, the results in Figure 7 indicate that the proposed framework can make systems much more resilient to failure and improve the real-time adaptiveness of systems. Rapid disturbance response earns safe and stable hardware operations that is essential for the applications of off-grid, microgrid with limited or no external resources. Additionally, faster stabilization minimizes the likelihood of subsequent failures propagating in a cascading manner, which also increases system reliability as a whole. In closure, as shown in Figure 7, the proposed adaptive energy management framework can clearly provide better dynamic response and adaptability compared to previous methods. The achieved short settling time, low overshoot and good robustness against disturbances assures that the proposed control approach can offer a fast, reliable and robust solution for controlling hybrid PV–hydrogen energy systems under dynamic and uncertain environments.

(a) Dynamic Response



(b) Settling Time Comparison

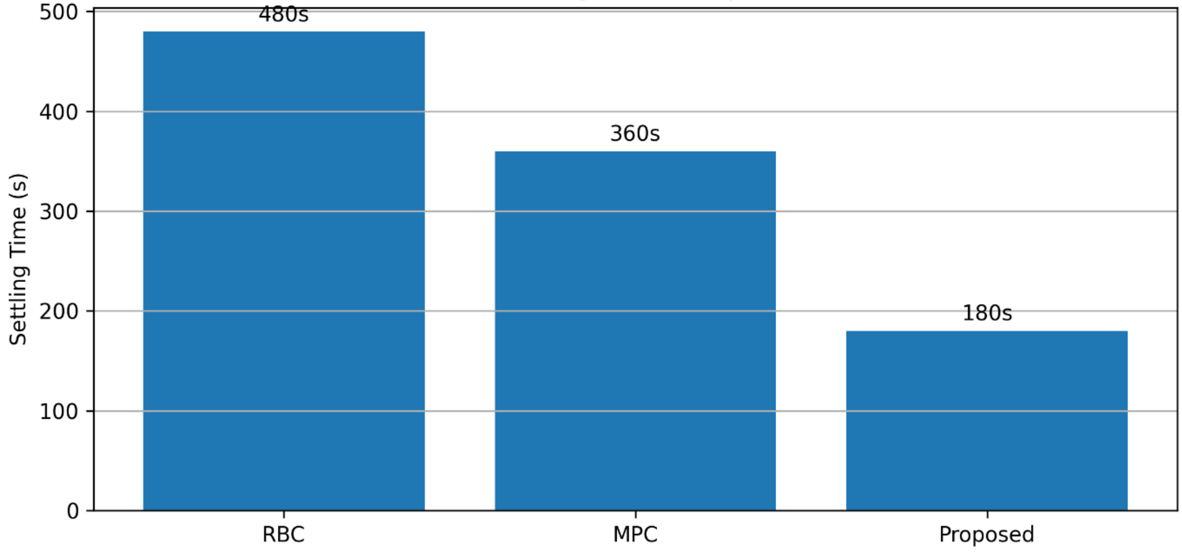


Fig. 7. (a) Dynamic response of the system to a sudden disturbance for RBC, MPC, and the proposed data-driven multi-objective optimization framework. The proposed method exhibits faster stabilization with reduced oscillations compared to MPC and RBC. (b) Settling time comparison, showing significantly faster convergence of the proposed method (2–4 minutes equivalent) relative to MPC (5–8 minutes) and RBC, confirming superior adaptability and real-time control performance under transient conditions.

Simulation studies confirm that the adaptive energy management and data-driven multi-objective optimization framework provide an effective and technical convenient approach for hybrid PV–hydrogen storage system operation. The framework fuses machine learning-based prediction, multi-objective optimization, and real-time adaptive control into one system to effectively relieve the key limitations of traditional energy management strategies by eliminating rigidity, exploring beyond local optimality, avoiding modeling dependencies and providing robust performance under uncertainty. This multi-layer architecture facilitates the optimal control of energy flows in both the electrical and hydrogen sectors, ensuring that renewable resources are fully exploited under dynamic and uncertain operating conditions while also sustaining system stability and reliability. Practically, the technique brings many relevant benefits that boost the performance of hybrid energy systems while making them more viable. First, the framework realizes significant enhancements in energy efficiency and operational cost reduction via optimal allocation of power among direct use, hydrogen production for storage and reconversion. This means that instead of curtailing excess renewable energy, it can be utilized fully resulting in improved system productivity. Second, it also shows greater reliability and resilience of off-grid and weak-grid supply systems when energy supply has to be maintained under variable generation as well as demand. In the redesign of energy systems with hydrogen storage serving as a long-duration energy buffer, the benefits can be further maximized to: greatly improve energy security by enabling continuous operation even during multi-day renewable generation lulls. Moreover, this framework also results in substantial reductions on component degradation and the maintenance needed for the same. The system achieves this by using degradation-aware optimization and avoiding unnecessary cycles that accelerate aging of components such as electrolyzers and fuel cells, allowing for longer component lifetime times while decreasing lifecycle costs. It is especially vital with deployment at scale where it can get costly to maintain and even more expensive to replace. In addition, the proposed architecture is scalable and flexible and therefore can be used in everything from stand-alone systems at small scales to interconnected microgrids and distributed energy networks. These benefits are useful features that make the framework widely applicable in many real-world scenarios. The strength of the system allows for an autonomous and reliable energy supply, leading to lower reliance on diesel generators and aiding sustainability in remote and island-based microgrids. It allows efficient utilization of renewable energy sources, reduces costs, and enhances the decarbonization potential in industrial systems powered by renewables. The framework is particularly relevant to smart energy communities that facilitate the coordinated management of distributed energy resources, which are critical for not only achieving energy efficiency but also providing resilience. In addition, in new hydrogen energy systems, the approach enables better combination between production, storage and use of hydrogen that is supporting the necessary transition toward hydrogen economies at large. In conclusion, these study results clearly indicate that the novel adaptive energy management framework presented in the paper enables significant performance benefits concerning all vital metrics of interest: efficiency, cost-effectiveness, reliability and robustness. Results show that the synergies of data-driven intelligence and multi-objective optimization enables a compelling approach to operate complex hybrid energy systems in real-world uncertainties. Instead of focusing on independent dimensions of performance in a piecemeal fashion as is done by traditional methods, the proposed approach provides a whole system solution for optimizing conflicting objectives while also being adaptable and resilient. The results of this study strongly advocate the use of intelligent and adaptive data-driven control strategies as a next-generation paradigm to achieve effective integration in hybrid PV–hydrogen energy systems. The developed approach is able to improve the performance of the system while promoting sustainable, resilient and highly efficient energy infrastructure essential for global marches towards clean energy transition and decarbonization.

IV. CONCLUSIONS

This work proposed a new adaptive energy management system (EMS) based on multi-objective optimization technique with data-driven model for hybrid PV–hydrogen storage systems working in off-grid and microgrid cases. The proposed approach integrates machine learning-based prediction, multi-objective optimization and real-time adaptive control into a single architecture to tackle the mix challenges of renewable intermittency, system uncertainty and coordinated multi-component operation. The framework developed allows for joint optimisation of key performance objectives such as renewable penetration, operating cost, energy efficiency, system reliability and components life. The proposed system operates on data-driven prediction models to anticipate fluctuations in solar generation and load demand; this enables proactive and adaptive decision-making. Integration of mechanisms that are aware of uncertainty also increase robustness and ensure stable as well reliable operation under stochastic environmental and operational conditions. According to the simulation results, the proposed method can provide significant improvements compared to traditional methods like rule-based control and model predictive control. Renewables used, operational costs and overall system efficiency all saw notable improvements. The framework also proved to be robust against the uncertainty, with smaller prediction errors and constraint violations as well as increased power stability. Notably, the suggested strategy also helped in reducing trickiness and degradation of components, further increasing the operational life time of essential system elements like electrolyzers and fuel cells.

The main contribution of this work also lies in the coordinated manner and multiple energy domain (electricity and hydrogen) direct-flow from the perspective of energy flow. By adding hydrogen storage as a seasonal energy buffer to a backup system, this increases flexibility in the overall scheme and addresses long-term renewable generation dropouts by providing this stored energy during drops where green resources cannot be relied on. Such ability is especially useful for off grid or remote applications where energy independence is paramount. Practically, the proposed framework provides a scalable and viable solution for next-generation energy system applications such as microgrids, islanded power systems, and renewable-powered industrial applications. It can be implemented in real-time and has a less computational burden, which makes it suitable for deployment in embedded control platforms.

Future works will also be dedicated to experimental verification with hardware-in-the-loop platforms, integration of the developed control framework with other storage technologies like battery systems, and extension to multi-agent frameworks for muscle control of interconnected microgrids. Moreover, implementing further sophisticated deep reinforcement learning approaches and digital twin driven predictive maintenance methodologies may additionally amplify system performance and robustness. In conclusion, the introduced data-driven multi-objective optimization framework not only provides a systematic and efficient method for operating hybrid PV-hydrogen energy systems but also advances sustainable, resilient and intelligent energy infrastructures relatively comprehensively.

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