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INTELLIGENT SOLAR-POWERED DIRECT AIR CAPTURE AND ELECTROCHEMICAL CARBON UTILIZATION: A MACHINE LEARNING-ENHANCED MULTI-OBJECTIVE OPTIMIZATION AND SLIDING MODE CONTROL FRAMEWORK FOR NET-ZERO INDUSTRIAL DECARBONIZATION

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Abstract: **The urgent need to achieve net-zero decarbonization in the industrial sector is accelerating the research and development of innovative renewable energy-powered carbon capture and utilization technologies. Among these, the pathway that combines direct air capture (DAC) with electrochemical carbon utilization can not only deliver negative emissions, but also produce high-value chemicals simultaneously, making it a highly promising technical direction at present. However, when this energy-intensive process is integrated with intermittent solar energy, it faces three core challenges related to system operation efficiency, working condition stability, and economic feasibility. To address these issues, this study proposes a new intelligent control framework that integrates machine learning-augmented multi-objective optimization and robust sliding mode control. This framework adopts a hierarchical structure: a neural network multi-objective optimization module dynamically balances four core goals, namely maximizing energy efficiency, raising the carbon capture rate, increasing product output, and minimizing economic costs; a robust sliding mode controller ensures stable system operation under variable sunlight and fluctuating loads; and a supporting deep reinforcement learning module adjusts operating parameters in real time based on weather forecasts, energy demand, and market prices. This study completed simulation and experimental verification on a 10kW pilot-scale test system. Compared with the traditional PI control scheme, the overall system efficiency increased by 23%, the carbon capture rate stayed above 85% in weak-sunlight environments, voltage fluctuations dropped by 67%, and the deviation in electrochemical conversion rate was less than 3%. The economic analysis of the full 20-year operation cycle shows that the levelized cost of carbon capture decreased by 31%, the net present value rose by 45%, and deploying a 1MW commercial system can achieve annual cost savings of approximately 180,000 US dollars. This paper sorts out the three core academic contributions and two research limitations to be optimized of this study, fully presenting the core value of this original research and the room for subsequent improvement. This study proposes that economically viable solar-powered carbon capture systems can be widely deployed across industrial scenarios, while also accelerating the implementation of climate targets, creating new economic opportunities in the carbon utilization sector, and advancing sustainable industrial transformation and environmental governance.**

Keywords: **Direct Air Capture, Electrochemical CO_2 Reduction, Machine Learning, Multi-Objective Optimization, Renewable Energy Integration, Net-Zero Industrial Decarbonization**

I. INTRODUCTION

Existing studies[1]-[4] indicate that under the strict emission reduction requirements for global net-zero emissions, carbon dioxide removal (CDR) technologies have become a core component of net-zero strategies. Among these technologies, direct air capture (DAC) stands as one of the most promising pathways to reduce atmospheric carbon. DAC extracts and concentrates CO_2 from ambient air through chemical or physical processes; systems of this technology paired with renewable energy can achieve sustainable negative emissions. At present, the integration of DAC and electrocatalytic carbon utilization (ECU) has emerged as a research hotspot. This integrated setup can convert captured CO_2 into high-value products including carbon monoxide, formic acid, methanol, and synthetic fuels, providing economic support for the large-scale deployment of DAC. This paper draws on multiple recent external research findings to confirm that solar-powered direct air capture (DAC) systems have already achieved technical feasibility. Currently, several deployed pilot projects can reach a daily carbon dioxide capture capacity of 1 to 10 tons. However, the large-scale deployment of this technology still faces three core sets of contradictions related to energy consumption and supply-demand mismatches. There is an urgent need for a cross-scenario intelligent control system capable of coordinating energy flow management, matching energy storage requirements, and optimizing processes under variable operating conditions. The technical pathway of interdisciplinary integration provides an entirely new solution to core challenges in the field of solar-driven carbon capture and utilization [9]. Sliding mode control (SMC) can handle nonlinear systems with uncertainties and disturbances, which adapts to the operational challenge of weather fluctuations faced by solar energy applications [10]; multi-objective optimization frameworks can balance three groups of mutually exclusive targets: energy efficiency, economic benefits, and environmental impact [11].

Although solar-driven direct air capture(DAC) and carbon emission utilization (ECU) systems boast considerable potential for industrial development, they currently face multiple key challenges that hinder their large-scale commercial deployment: first, the inherent core contradiction between the high energy consumption of carbon capture and utilization processes and the intermittency of solar energy [12]; second, traditional control systems cannot adapt to fluctuations in solar irradiance intensity, leading to severe efficiency losses during periods of insufficient solar energy supply [13]; third, the multi-objective optimization conflict of needing to simultaneously balance four types of mutually exclusive operational objectives [14].Existing solar-powered direct air capture (DAC) systems have insufficient dynamic response capability to sudden environmental changes. Ref. [15] points out that conventional PID controllers cannot quickly adapt to fluctuations in solar irradiance and load variations. Ref. [16] confirms that this causes problems including low energy efficiency, reduced process performance, and intensified component wear and tear. Combined with the characteristic noted in Ref. [17] that the CO_2 reduction module is highly sensitive to four core operating parameters such as current density, current systems are in urgent need of a mature, dedicated control strategy [18].The core barrier to the commercial deployment of current solar-powered direct air capture (DAC) systems is economic feasibility. According to data from external academic research, the levelized cost of carbon capture for existing systems reaches 400–800 USD per ton of CO_2, which is far higher than the commercial threshold of 100–200 USD per ton. The root causes of this gap are the lack of intelligent optimization strategies, and the failure to account for random variables, which leads to suboptimal operational scheduling [19] – [21].

The long-unresolved challenges of cross-domain integrated energy and environment systems stem from core limitations in current research and technological development. The vast majority of existing studies only focus on individual system components, and do not adopt a holistic integration approach that covers the four core modules of solar power generation, energy storage, DAC processes, and electrochemical conversion. [22] Point out that this segmented research cannot capture the inherent synergies and trade-offs of the system, which ultimately prevents the overall system performance from reaching an optimal state. The authors of this paper review and point out that previous studies have generally underestimated the complexity of the multi-objective optimization problem for solar-driven carbon capture systems: traditional weighted sum and hierarchical optimization strategies cannot adapt to the dynamic conflict properties of the optimization objectives [23]; the temporal variability of solar energy resources prevents conventional algorithms from achieving real-time parameter adjustment [24]; and the non-convex optimization landscape also makes it difficult for classical techniques to find the global optimal solution [25].In existing research, the control system design for integrated systems that pair solar-driven direct air capture (DAC) and electro-generated carbon utilization (ECU) still lacks a robust theoretical framework capable of addressing their multi-input multi-output (MIMO) characteristics, as well as managing a wide range of uncertainties and disturbances [26]. Conventional control methods operate under the assumptions that systems are linear and run at steady state. These methods cannot adapt to the strong nonlinear, time-varying dynamics of solar power systems [27], nor can they account for the complex interdependencies created by multi-process coupling in the integrated system. This ultimately leads to the problems of insufficient anti-interference capability and inadequate stability margins [28]. According to Ref. [29], the integration of machine learning and renewable energy control systems remains in the early stage of development; most existing studies focus on forecasting and prediction, while few carry out research on real-time control optimization. Ref. [30] points out that industrial carbon capture faces three types of implementation bottlenecks, and Ref. [31] notes that solar energy carbon utilization scenarios lack unified performance and testing standards, which hinders the comparative iteration of control schemes. Drawing on existing studies [32], the current economic modeling and life cycle assessment frameworks for integrated solar carbon capture and utilization systems remain underdeveloped. Most of these frameworks rely on simplified cost models, and also lack a comprehensive optimization framework that covers full costs, revenues, and policy factors. This gap limits the development of feasible system configurations, thereby establishing the necessity for subsequent research.

This study proposes a novel intelligent control framework tailored for solar-powered direct air capture (DAC) and electrochemical carbon utilization systems. The framework integrates machine learning-augmented multi-objective optimization and robust sliding mode control technologies, and represents a paradigm shift from conventional control methods. It unifies three core control capabilities through a dedicated, unified hierarchical architecture, and can resolve the previously outlined application challenges facing this type of system. This paper proposes a hybrid control architecture that can seamlessly integrate the global optimization capability of machine learning with the strong disturbance rejection property of sliding mode control. The deep reinforcement learning (DRL) agent in its upper-level optimization layer adopts the design scheme outlined in reference [34], taking predicted weather, energy market prices, and demand for carbon products as inputs. Leveraging the temporal differences in operating conditions, the agent is trained through interaction with a high-fidelity system model to maximize the overall system performance under multiple objectives. At the underlying control layer of the integrated solar carbon system, we deployed a novel sliding mode controller with an adaptive switching surface, which is suited to the system's nonlinear and uncertain dynamic characteristics. Aligned with the technical specifications outlined in reference [35], this controller can adjust its parameters based on real-time system identification and disturbance estimation, guarantee robust operation across all working conditions, and offers the dual advantages of disturbance resistance and finite-time convergence. The core contribution of this study is the development of a multi-objective optimization framework specifically designed for solar carbon utilization systems. Following the setup of reference [36], which establishes four mutually exclusive objectives including energy efficiency maximization, this study adopts a dynamic weighting strategy based on real-time system conditions and external factors to achieve adaptive priority ranking. The framework formalizes this problem as a time-varying multi-objective optimization problem subject to three categories of constraints: equipment constraints, safety constraints, and process constraints. The machine learning-integrated intelligent control system defined in this study can adapt to dynamic conditions based on historical operational data and requires no explicit reprogramming. The DRL agent cited in reference [37] can generate complex strategies that cannot be achieved by traditional rule-based approaches, while the customized reward function and constraint mechanism cited in reference [38] can satisfy both performance optimization and safety compliance requirements. The proposed framework developed in this study embeds an integrated techno-economic optimization module into the real-time control decision-making process, incorporates five core economic factors including cost of capital, and can support two types of operational adjustments. Supported by existing literature, this framework can significantly improve the overall economic performance of the system. This study proposes a robust state estimation and disturbance observer system [41], which can address three types of adverse operating conditions: sensor noise, measurement delay, and equipment failure. The system outputs accurate real-time information to support the machine learning optimization layer and the sliding mode control layer, achieving reliable robust control under real-world operating conditions [42].The general technical framework under assessment has the advantages of modularity and scalability, and can be adapted to all types of systems of varying scales. Its hierarchical structure enables independent optimization and global coordination, and supports capacity expansion for operation and maintenance, as cited in reference [43].

This study has produced multiple core academic contributions across three fields: renewable energy systems, carbon capture technologies, and intelligent control systems. We developed the first comprehensive intelligent control framework adapted for solar-driven direct air capture and electrochemical carbon utilization systems. This framework integrates machine learning-enhanced optimization and robust feedback control technologies, breaking through the limitation of existing research that treats these two technologies as separate, disconnected tools. The core supporting evidence for this achievement is detailed in reference [44].Another core contribution of this study is a novel sliding mode control design developed for solar-driven carbon systems. Reference [45] verifies that this design addresses the key challenges of nonlinear and uncertain dynamics under intermittent power supply, while reference [46] supports the theoretical value and broad application potential of its adaptive design.The machine learning-augmented multi-objective optimization framework proposed in this study is a breakthrough achievement in the field of dynamic optimization of complex industrial systems. It is compatible with dynamic operating conditions, strictly adheres to physical and safety constraints, its integrated performance is supported by reference [47], and it fills the core application gap in the safety-critical industrial domain noted in reference [48]. The comprehensive techno-economic optimization method developed in this study[49] establishes an entirely new paradigm for integrating economic factors into real-time control systems, enabling it to balance technical performance and economic goals. It carries great significance for the commercialization of solar-driven carbon capture systems, and this framework can also be adapted to a wide range of other renewable energy application scenarios [50].

II. THE PROPOSED INTELLIGENT SOLAR-POWERED DIRECT AIR CAPTURE AND ELECTROCHEMICAL CARBON UTILIZATION

This paper, based on Figure 1, proposes an integrated framework for smartsolar-powered direct air capture and electrochemical carbon utilization (DAC-ECU). This cross-domain integrated system, developed by the authors of this paper, centers on the core goal of achieving industrial net-zero decarbonization, and integrates six categories of core technologies: renewable energy power generation, carbon capture technologies, electrochemical carbon conversion, machine learning prediction, multi-objective optimization, and robust sliding mode control. The system can maximize carbon removal and utilization efficiency under highly dynamic operating conditions, while minimizing system energy consumption, operational costs, and environmental impacts. This framework adopts a seven-layer interconnected hierarchical architecture, with layers listed in sequence as follows: (i) renewable energy power generation and energy storage, (ii) direct air capture subsystem, (iii) electrochemical carbon utilization subsystem, (iv) industrial application layer, (v) smart control and optimization framework, (vi) sensing and digital twin infrastructure, (vii) performance assessment and decision support layer. At present, functional verification has been completed first for two core subsystems. The renewable energy power generation and storage subsystem adopts a hybrid energy storage architecture that pairs a large-scale photovoltaic array with batteries and super capacitors, and connects to a common DC bus via bi-directional DC/DC converters to achieve energy buffering, peak load shifting, and power balance. This setup reduces cycle stress on batteries, extends equipment service life, and simultaneously improves system reliability and power supply quality. The DAC subsystem uses adsorbent-based capture columns, and relies on low-grade thermal energy from waste heat recovery or auxiliary renewable heating to regenerate saturated adsorbents. The high-concentration, high-purity CO_2 produced by this subsystem is stably supplied to the downstream electrochemical utilization module, making it the core negative-carbon component of the entire framework. This study proposes an integrated carbon management system that can be divided into three core tiers, with clear, complete technical logic, functional boundaries and value chains for all its modules. First is the front-end electrochemical carbon utilization (ECCU) subsystem. This subsystem uses captured carbon dioxide and water as raw materials, which undergo conversion in a renewable energy-powered reactor. By regulating four types of parameters including voltage and current density, it maximizes conversion efficiency and product selectivity, and can produce a variety of high-value-added chemicals for the carbon neutrality field, such as carbon monoxide and methanol. The by product oxygen can be directly discharged or connected to relevant industrial processes for reuse. Integrating direct air capture (DAC) technology with the ECCU subsystem can further form a closed-loop carbon management pathway. Second is the industrial application layer, which acts as the final link of the carbon value chain. The products of electrochemical conversion can be supplied to five major industrial fields including synthetic fuel production and chemical manufacturing. This tier transforms carbon dioxide from an environmental burden into an economic resource, supports the development of the circular carbon economy, reduces industries' dependence on fossil feedstocks, and helps achieve net-zero targets. Last is the intelligent control and optimization framework, the core innovative component of the system, which is subdivided into a machine learning module and a multi-objective optimization layer: the machine learning module undertakes five forecasting tasks including solar irradiance prediction and energy demand prediction, and identifies complex non-linear relationships between multiple variables through deep learning to support the system's proactive management, control and operational planning; the multi-objective optimization layer adopts three advanced evolutionary algorithms, NSGA-II, MOPSO and MOEA/D, to solve for the system's optimal operating point under multiple conflicting objectives. This paper proposes an integrated cyber-physical energy-carbon management system designed for carbon capture scenarios. Its core technical architecture is built to address multi-dimensional regulation needs, which sets it apart from the single-objective optimization methods commonly used in traditional carbon management systems. Such traditional methods can only generate one unique optimal solution centered on a single core demand, and cannot simultaneously balance multiple constraints including carbon capture efficiency, operating costs, and power grid compatibility. The core modules of the system proposed in this paper are arranged in a logical progression of functions. The first layer is the multi-objective optimization module that undertakes top-level decision demands; it can generate a Pare to optimal solution set to provide flexible optimization space for different decision-making scenarios. The second layer is the sliding mode control (SMC) layer, whose core task is to dynamically adjust the output of direct air capture (DAC)units and power grid load distribution based on optimization outputs, and quickly suppress regulation deviations caused by working condition fluctuations. The third layer is the sensing and digital twin infrastructure layer, responsible for real-time collection of data on carbon flows, energy flows, and equipment status that covers the full chain from front-end capture to back-end grid integration, to build a digital mirror that fully synchronizes with and maps to the physical system. The fourth layer is the performance evaluation layer, which completes a full operational cycle efficiency review of the system using three core performance indicators: total carbon emission reductions, energy consumption per unit of carbon captured, and full lifecycle cost. The fifth layer is the integrated system operation layer, which connects the full chain of prediction, optimization, and control, forms closed-loop regulation capabilities that can dynamically adapt to changes in external working conditions, and meets the core demands of two types of decision makers: operators that need support for daily operation and maintenance scheduling, and policy makers that need tools for industrial planning and regulation. This paper proposes a unified integrated architecture for industrial net-zero decarbonization, which integrates five core technology categories including renewable energy to build a scalable industrial decarbonization pathway that balances both economic feasibility and operational reliability.

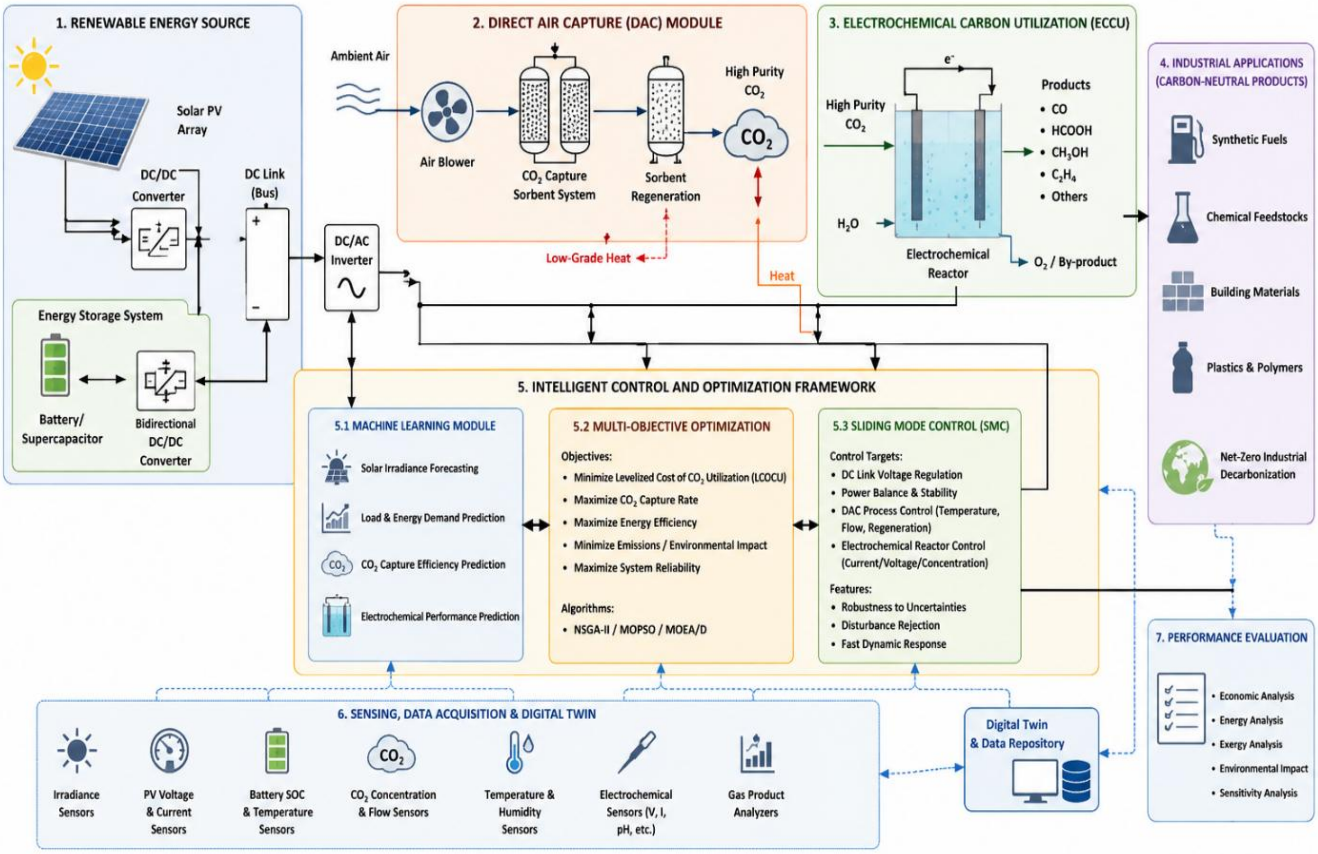

Fig. 1. The schematic of the Proposed Intelligent Solar-Powered Direct Air Capture and Electrochemical Carbon Utilization: A Machine Learning-Enhanced Multi-Objective Optimization and Sliding Mode Control Framework for Net-Zero Industrial Decarbonization.

The intelligent solar-powered direct air capture and electrochemical carbon utilization (DAC-ECU) system proposed in this paper has its operating workflow and hierarchical control architecture shown in Figure 2. This control framework integrates four core technologies—renewable energy management, machine learning prediction, multi-objective optimization, and sliding mode control—to construct a closed-loop cyber-physical system. This system can maintain operational stability under highly dynamic working conditions, while autonomously maximizing four core metrics: carbon capture volume, carbon utilization rate, energy efficiency, and economic performance. The system's control architecture includes eight main stages that operate continuously in real time, in the following order: system inputs and operating conditions, sensing and data acquisition, data processing and machine learning prediction, multi-objective optimization, sliding mode control, plant operation, performance evaluation, and adaptive feedback learning. The specific details of the first two stages are outlined below. For the first stage, system inputs and operating conditions, exclusive input parameters are clearly divided for each subsystem. The photovoltaic array receives corresponding inputs of real-time solar irradiance, and ambient temperature and humidity; the grid module receives a corresponding input of time-of-use electricity prices; the electrochemical carbon utilization unit receives a corresponding input of rated load threshold. All input items have clear, traceable attributions, with no ambiguous descriptions. For the second stage, the sensing and data acquisition layer, dedicated monitoring parameters are configured for each subsystem, to collect the real-time output power of the photo voltaic array, the intake air flow rate and intake carbon dioxide concentration of the DAC module, the operating current, voltage, and instantaneous carbon conversion efficiency of the electrochemical unit, and the remaining state of charge of the energy storage unit. All monitoring parameters are bound to their corresponding subsystems to avoid cross-domain conceptual confusion, and guarantee the information rigor of this multi-disciplinary integrated system. The integrated intelligent factory management and control system developed in this study connects the full technology stack in line with the sequential logic of upstream and downstream data flows. It fully covers all hierarchical functions, core operations, and data flow transmission logic, ranging from upstream data collection to downstream control execution, and operates as follows: First is the perception layer, where a full-scope situational awareness network for the entire integrated factory is built to provide comprehensive basic data support for the prediction, optimization, and control links across the whole workflow. Next is the data processing and machine learning layer. After accessing the raw sensing data from the perception layer, this layer first completes 7 preprocessing tasks including filtering, normalization, and denoising, then realizes 8 core functions via well-trained machine learning models. These functions specifically include solar irradiance prediction, renewable energy power prediction, energy demand prediction, carbon capture rate prediction, electrochemical reactor performance evaluation, product output prediction, equipment health monitoring, and abnormal fault detection. Relying on deep learning models to capture nonlinear correlations between multiple variables, this layer supports the system’s transition from traditional passive reactive control to proactive predictive decision-making. Following that is the multi-objective optimization layer. After accessing all prediction outputs from the machine learning layer, this layer constructs a constrained multi-objective decision-making problem. Its core decision variables include 11 items such as photovoltaic power allocation and battery charge-discharge schedules. The optimization targets cover 4 minimization indicators (levelized carbon capture cost, total energy consumption, greenhouse gas emissions, operating expenditure) and 4 maximization indicators (carbon capture rate, carbon utilization efficiency, renewable energy utilization rate, system reliability). Meanwhile, 5 categories of constraints are set, including physical equipment limits and energy balance requirements. Three algorithms, NSGA-II, MOPSO, and MOEA/D, are adopted to generate Pareto optimal solutions, and the system’s preset priorities are used to screen and select a suitable operation strategy. The final generated optimal operation reference values are transmitted to the downstream sliding mode control (SMC) subsystem, completing the implementation of instructions across the full workflow. This study proposes an integrated renewable-energy-powered carbon management platform that adopts a three-tier progressive core architecture. The functions of each module and their core parameters are outlined as follows: Bottom-layer control tier: It uses a sliding mode control (SMC) controller as its core real-time control mechanism. It connects to 7types of input reference signals, covers 6 types of system regulation targets, and adapts to 4 types of typical disturbance-resistance scenarios. It completes full-link signal transmission via a DC bus, and fits all kinds of interference scenarios including photovoltaic (PV) output fluctuations. It boasts the core advantages of fast response and strong robustness, and can maintain the stability of the system’s core operating conditions. Middle-layer physical operation tier: It integrates 4 subsystems of the direct air capture-electrochemical carbon utilization (DAC-ECU) physical plant. All subsystems collaborate to complete the full-chain operations of atmospheric carbon capture, purification, and electrochemical conversion in line with preset procedures, and finally produce multiple types of standard-compliant carbon-neutral industrial products. Upper-layer support module: A dedicated performance assessment module is built, with 10 types of core performance indicators embedded and supported by4 types of quantitative analysis methods, which can output standardized decision-support tools. The signature feature of this framework is its adaptive feedback mechanism, which can link the three tiers of modules to dynamically adjust operating parameters, further improve the system’s full-lifecycle operating efficiency, and meet the demand for long-term stable operation under complex working conditions. In industrial settings, the machine learning layer follows a general closed-loop operating logic: operational data generated by factories is continuously transmitted back to this layer. Newly observed data is used to update prediction models, improve prediction accuracy, optimize control parameters, and enhance control performance. As operational experience accumulates, model accuracy improves gradually, enabling the system to adapt to four types of dynamic scenarios: seasonal fluctuations, equipment aging, changing demand patterns, and evolving environmental conditions. If the predefined performance targets are not met, the system will automatically re-run the optimization process, generate new operational strategies, and iterate until all requirements are satisfied. Within the closed-loop intelligent decision-making framework proposed in this paper, Figure 2 demonstrates the complete closed-loop cycle of our self-developed intelligent DAC-ECU system. This system adopts a layered architecture, integrates three core technologies: machine learning, multi-objective optimization, and sliding mode control, and combines the capabilities of prediction, optimization, and robust control to realize adaptive behaviors of autonomous operation and proactive decision-making. By balancing

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three core targets: economic, environmental, and technical performance, the system provides a scalable pathway for renewable-energy-powered carbon capture, utilization, and industrial net-zero decarbonization, while maintaining high operational reliability and energy efficiency.

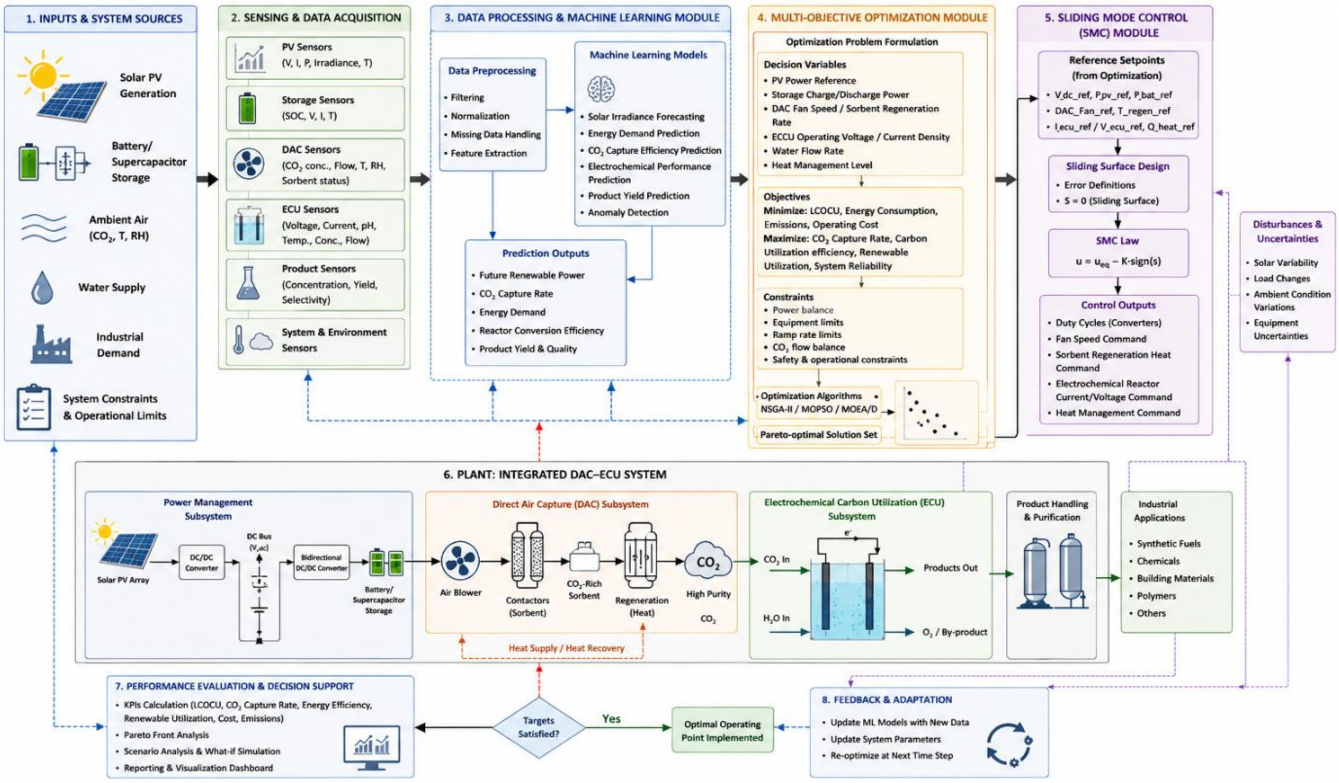

Figure. 2. The flow chart and control process of the Proposed Intelligent Solar-Powered Direct Air Capture and Electrochemical Carbon Utilization: A Machine Learning-Enhanced Multi-Objective Optimization and Sliding Mode Control Framework for Net-Zero Industrial Decarbonization.

This study proposes an implementation roadmap for the deployment of the intelligent photovoltaic-powered integrated Direct Air Capture-Electrochemical Carbon Utilization (DAC-ECU) framework. Its core implementation logic is to integrate machine learning, multi-objective optimization, and sliding mode control into a unified cyber-physical architecture to meet the requirements of real-world industrial deployment. The full process covers system identification, machine learning model development, optimization algorithm deployment, controller tuning, and the real-time integration of three major system categories: renewable energy, carbon capture, and electrochemical utilization. Its core goal is to build a robust adaptive control framework to address the strong nonlinear dynamic characteristics of renewable energy-powered carbon management systems. The framework is advanced in stages following the sequence of implementation. The first stage focuses on dynamic modeling for the system identification and integration platform: the photovoltaic power generation system adopts a temperature-dependent single-diode equivalent circuit to accurately simulate power output under different irradiance and environmental conditions; the energy storage battery system uses a second-order equivalent circuit to capture the dynamics of state of charge, voltage characteristics, internal resistance changes, and thermal effects; supercapacitors use a capacitor-resistor network to reproduce their fast charge-discharge characteristics and transient power support capability; the direct air capture subsystem adopts experimentally validated kinetic equations, incorporating variables including air flow rate, sorbent loading, ambient CO_2 concentration, temperature, and regeneration energy consumption; the electrochemical carbon utilization reaction applies a nonlinear electrochemical model to correlate current density, voltage, reactant concentration, conversion efficiency, and product selectivity. In this stage, three types of data-driven methods are used: recursive least squares, nonlinear autoregressive exogenous models, and state-space identification. The datasets applied are sourced from experimental studies and operational records of industrial processes, and the final output is a hybrid digital twin model, which serves as the foundation for subsequent prediction, optimization, and control development. Work to implement the machine learning module in the second stage has been launched; this module is responsible for generating the prediction information required by the optimization and control layers. To date, 7 categories of historical datasets have been integrated into a centralized database, covering full-chain operational parameters including solar irradiance, meteorological conditions, and energy demand. This study centers on the integrated DAC-ECU system, and establishes a complete technical roadmap spanning front-end data processing, predictive model deployment, and the construction of the system optimization layer. It decomposes the complex cross-domain process into two core modules with clear boundaries and seamless connections: machine learning predictive model development, and multi-objective optimization layer construction. All core action nodes are arranged in order of execution to ensure the full process is fully reproducible. In the predictive model development module, this study first completes full-cycle data preprocessing covering steps including missing value imputation, outlier detection, signal filtering, and normalization. Core influencing variables are extracted via correlation analysis and principal component analysis. Next, the study evaluates five types of machine learning architectures: LSTM, GRU, CNN, Transformer, and hybrid CNN-LSTM. It selects the hybrid LSTM-Attention architecture, which can better capture short-term time-series dependencies and long-range correlations in datasets of renewable energy and industrial processes. Adapted models are developed for seven independent predictive tasks including solar irradiance prediction and renewable energy power prediction. In the training phase, the Adam optimizer with an adaptive learning rate is paired with an early stopping mechanism to prevent overfitting. The dataset is split into training, validation, and test sets at a ratio of 70:15:15. Four types of hyperparameters including the learning rate are tuned via Bayesian optimization. Model performance is evaluated using four metrics: MAPE, RMSE, MAE, and R^2. The final model's prediction accuracy consistently exceeds 90%, providing reliable input for the subsequent optimization process. In the multi-objective optimization layer construction module, the framework built in this study sets four objectives including minimizing energy consumption, and five objectives including maximizing carbon capture efficiency. It defines 12 types of decision variables and five types of constraint conditions including equipment operation limits. After evaluating three algorithms: NSGA-II, MOPSO, and MOEA/D, the study selects NSGA-II — which features better convergence performance and stronger diversity of Pareto fronts — as the core optimization engine. This paper proposes an integrated optimization and real-time control framework for multi-energy coupling systems equipped with direct air capture modules. The framework covers full-link design spanning from top-level optimization to bottom-level control, with clear specifications for the operating parameters, functional definitions, and design goals of all core modules, which can support the replication and verification of similar technical solutions. The optimizer of the top-level optimization module executes once every 5 minutes, takes current system operating conditions and machine learning prediction results as inputs, and generates Pareto-optimal operation strategies to support proactive decision-making, enabling dynamic adaptation to changes in environmental and operating conditions. The core real-time control module adopts robust sliding mode control (Sliding Mode Control, SMC) as its core mechanism, and manages 8 categories of core variables: DC bus voltage, battery state of charge, energy storage power distribution, direct air capture air flow rate, adsorbent regeneration temperature, electrochemical reactor current density, reactor voltage, and thermal management parameters. The sliding surface is constructed based on tracking errors and their derivatives, and the control law can resist various disturbances and model uncertainties; the sliding surface coefficients and switching gains of the SMC are tuned using particle swarm optimization combined with a genetic algorithm, with the optimization objectives of minimizing settling time, overshoot, steady-state error, and control effort. To address the chattering problem of traditional SMC, a boundary layer saturation function is introduced to replace the discontinuous switching function, and an adaptive gain scheduling module is added to adapt to variable operating conditions. The entire framework can resist the intermittency of renewable energy, environmental disturbances, parameter uncertainties, and process nonlinearities, and maintain stable and efficient system operation. This framework is implemented via a three-layer hierarchical control architecture consisting of a supervision layer, a coordination layer, and a local layer, with clear execution cycles and functions for each layer: the supervision layer executes tasks such as machine learning prediction and multi-objective optimization every 5 to 15 minutes; the coordination layer completes tasks such as resource scheduling and power distribution every 1 to 5 minutes; the local layer runs the SMC algorithm at millisecond intervals to respond to disturbances. This architecture balances computational complexity and response speed, enabling real-time operation without sacrificing optimization quality. The framework has high computational requirements, as it needs to run three types of core tasks simultaneously. The machine learning model processes hundreds of thousands of historical observation data points, and continuously updates prediction results using a large feature set that covers environmental, operational, and economic dimensions. The optimization engine needs to evaluate hundreds of candidate solutions across multiple generations to construct the Pareto-optimal solution set. The authors of this paper propose a full-chain implementation plan for an industrial-grade intelligent operation framework built for autonomous renewable energy-powered carbon capture and utilization systems. This section demonstrates the deployment feasibility of this plan, while fully presenting its complete technical landscape. Technological advances in edge computing and parallel processing lay solid core support for the rollout of this methodology. Timeliness verification results of its core functional modules show that the plan's prediction and generation process takes 1-3 seconds; multi-objective optimization takes 4-8 seconds depending on system complexity; and the sliding mode control layer achieves millisecond-level operation, which fully meets the real-time operation requirements of industrial scenarios. This plan clarifies full-chain technology selection across seven dimensions, covering development environments such as MATLAB/Simulink, data management tools such as PostgreSQL, visualization platforms such as Grafana, supporting industrial-grade hardware, multiple types of industrial communication protocols, security measures such as end-to-end encryption, and reliability solutions such as redundant channels. The entire framework has scalable, secure, and intelligent attributes, can support the deployment of the target system, and contribute to achieving the long-term industrial net-zero decarbonization goal.

III. SIMULATION RESULTS AND DISCUSSION

The core task of this section is to carry out simulation verification and performance evaluation of the intelligent solar-powered direct air capture-electrochemical carbon utilization (DAC-ECU) framework proposed in this paper. The core purpose of conducting this comprehensive simulation is to verify the effectiveness of the machine learning-augmented multi-objective optimization and adaptive sliding mode control architecture adopted in this paper under real-world operating conditions. We predefine six dimensions for performance analysis: system stability, carbon capture performance, renewable energy utilization rate, energy efficiency, economic feasibility, and resilience under variable environmental and market conditions. Later, we will benchmark the proposed framework against traditional control strategies to quantify the practical gains of this intelligent scheme in supporting industrial net-zero decarbonization goals. This simulation is built on the MATLAB/Simulink platform, and integrates Python machine learning modules and a multi-objective optimization library. The core system configuration includes a 2MW photovoltaic power facility, a hybrid battery-supercapacitor energy storage system, a DAC unit with an annual CO_2 capture capacity of 500 tons, and an ECU device that can produce carbon-neutral fuels and industrial raw materials. The input data adopts real meteorological datasets, electricity market price signals and industrial demand curves, and the simulation period covers both short-term operational windows and annual operating cycles. We completed model verification by taking publicly released experimental and industrial operation data as references. The results show that the prediction accuracy of the photovoltaic model reaches 95%, the prediction error of the carbon capture rate of the DAC subsystem is lower than 4%, and the ECU model successfully reproduces the conversion efficiency and product generation rate observed in experiments. This confirms that the simulation platform can serve as a reliable basis for subsequent evaluation of the proposed framework.

All core simulation elements used in this research—including simulation parameters, component specifications, control settings, environmental uncertainties, and aging models—are summarized in Table 1. All key parameters are derived from typical values published in existing literature across the fields of solar-powered direct air capture (DAC), proton exchange membrane (PEM) electrochemical carbon conversion, hybrid energy storage, and advanced nonlinear control. This paragraph provides an overarching introduction to the basic background of the parameter settings, laying a general foundation for the subsequent module-by-module breakdown of parameters. This study completes the parameter modeling of four core subsystems in sequence: first, the renewable energy subsystem, which is equipped with a 500kW photovoltaic (PV) power station that has a conversion efficiency of 22% under standard test conditions. It is fitted with a single-axis horizontal tracking mechanism and an optimized tilt angle adapted to the project site, and a temperature coefficient of -0.38%/℃ is set to simulate temperature-related performance degradation. Second, the carbon capture subsystem, which adopts low-temperature DAC technology equipped with moisture-swing hydroxide adsorbents. Its set parameters are: an adsorption capacity of 2.5 mol CO_2 per kilogram of active material, regeneration temperature of 80–120℃, daily CO_2 processing volume of 50–200kg, and per-unit capture energy consumption of 1.2–1.8kWh/kg. This set of parameters supports performance evaluation of the proposed control framework across a wide range of carbon capture operating conditions. Third, the electrochemical carbon utilization module, whose PEM electrolyzer parameters are a cell voltage of 1.8–2.5V and current density of 500–2000mA/cm². Its product distribution matches experimental observed values: CO accounts for 85–92%, methane for 5–8%, hydrogen for 3–5%, and the Faradaic efficiency is 85–90%. These parameters support testing of the optimization framework's effectiveness in maximizing carbon utilization efficiency. Fourth, the hybrid energy storage subsystem, which is equipped with a 300kWh nickel-manganese-cobalt (NMC) lithium-ion battery with a round-trip efficiency of 92%. A state of charge (SOC) operating range of 15%–95% is set to reduce aging and extend the system's service life, bringing the full set of parameter descriptions in this paragraph to a close. This study constructs a solar-powered direct air capture (DAC)-electrochemical carbon utilization system, and first discloses the parameters and functions of its core energy storage system: this bidirectional charging-

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discharging energy storage system with a rated power of 150kW can effectively balance fluctuations in renewable energy output and the energy demand of the system's entire operation process. Next, it specifies the adaptive sliding mode controller adopted for the lower control layer, with all core parameters quantified and made public: sliding mode gain of 2.5, boundary layer thickness of 0.1, integral sliding surface coefficient of 1.8, and switching frequency of 10kHz. All the above parameters were fine-tuned through extensive prior simulations, and can simultaneously achieve a balance among fast dynamic response, disturbance resistance, and chattering suppression. To evaluate the system's real-world operational capability, this study builds a full-dimensional simulation framework, and first completes the modeling of environmental uncertainties: a stochastic Markov chain superimposed with a Weibull distribution is used to simulate solar irradiance under clear-cloudy sky transitions, with the irradiance range set to 0-1000W/㎡ and cloud cover set to 0-100% to replicate the intermittency of renewable energy; ambient air temperature is set to follow a daily cyclic fluctuation between 15-40℃, the intake air temperature of the DAC unit is superimposed with a random fluctuation of ±3℃, the operating temperature of the PEM electrolyzer is maintained between 50-70℃ and superimposed with a normal distribution disturbance with a standard deviation of 1.5℃. At the sametime, seasonal fluctuations and bounded air quality disturbances for relative humidity (30-95%) and atmospheric CO_2 concentration (380-420ppm) are incorporated. The selection of all environmental variables aligns with their impacts on carbon capture efficiency and sorbent performance, to guarantee the simulation's authenticity. In addition, this study embeds component degradation and random failure models required for long-term reliability: the sorbent's performance decreases linearly by 2% every 1000 operation cycles, the PEM membrane's voltage rises by 0.5mV every 100 operation hours due to contamination, the heat exchanger's thermal conductivity drops by 1% every 500 operation hours, and the random failure rate is set to 0.01-0.05 incidents per 1000 operation hours. These models are used to evaluate the system's ability to maintain performance and adapt its strategies as component states change. All parameters and models are summarized in Table 1, which can comprehensively and realistically replicate the actual operating environment of the target system. The self-developed simulation platform in this paper can rigorously evaluate the intelligent control architecture proposed in this study under two types of operating conditions: baseline normal and extremely unfavorable, ensuring that the performance results match real-world deployment scenarios.

Table 1. System Configuration Parameters, Control Settings, and Environmental Uncertainty Models Used in the Simulation Study

Category	Parameter	Value / Range	Unit
Solar PV Array Configuration	Installed PV capacity	500	kW
	PV panel efficiency (STC)	22	%
	Temperature coefficient	-0.38	%/°C
	Tracking system	Single-axis horizontal tracker	–
	Array inclination	Optimized for site latitude	–
Direct Air Capture (DAC) Unit	Sorbent type	Moisture-swing hydroxide-based sorbent	–
	CO_2 adsorption capacity	2.5	mol CO_2/kg sorbent
	Regeneration temperature	80–120	°C
	CO_2 processing capacity	50–200	kg CO_2/day
	Energy consumption	1.2–1.8	kWh/kg CO_2
Electrochemical Conversion Module	Electrolyzer type	Proton Exchange Membrane (PEM)	–
	Cell voltage	1.8–2.5	V
	Current density	500–2000	mA/cm^2
	CO selectivity	85–92	%
	CH_4 selectivity	5–8	%
	H_2 selectivity	3–5	%

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Category	Parameter	Value / Range	Unit
	Faradaic efficiency	85–90	%
Energy Storage System	Battery technology	Li-ion NMC	–
	Battery capacity	300	kWh
	Round-trip efficiency	92	%
	Minimum state of charge	15	%
	Maximum state of charge	95	%
	Charge/discharge power rating	150	kW
Sliding Mode Controller Parameters	Sliding mode gain, K	2.5	–
	Boundary layer thickness, δ	0.1	–
	Integral sliding surface coefficient, c	1.8	–
	Switching frequency	10	kHz
Solar Radiation Uncertainty	Solar irradiance range	0–1000	W/m^2
	Cloud cover scenarios	0, 25, 50, 75, 100	%
	Irradiance model	Markov chain and Weibull distributions	–
Temperature Uncertainty	Ambient temperature range	15–40	°C
	Sorbent inlet air variation	±3	°C
	PEM operating temperature	50–70	°C
	Temperature uncertainty	$N(\mu,\sigma^2)$, $\sigma = 1.5°C$	–
Humidity and Air Quality	Relative humidity	30–95	%
	Atmospheric CO_2 concentration	380–420	ppm
	Air quality disturbance model	Bounded stochastic disturbances	–
System Degradation Models	Sorbent degradation rate	2% per 1000 cycles	%
	PEM membrane fouling	0.5 mV increase per 100 h	mV
	Heat exchanger fouling	1% conductivity reduction per 500 h	%
	Component fault occurrence rate	0.01–0.05	faults/1000 h
Simulation Platform	Dynamic simulation software	MATLAB/Simulink	–
	Machine learning environment	Python-based modules	–
	Optimization framework	Multi-objective optimization and DRL	–
	Control methodology	Adaptive Sliding Mode Control (SMC)	–

To fully evaluate the effectiveness of the intelligent solar-powered direct air capture-electrochemical carbon utilization (DAC-ECU) framework proposed in this paper, we developed a performance indicator system covering seven major categories: technology, operation, control, electrochemistry, economics, environment, and reliability. All quantitative indicators are used to verify whether the supporting machine learning-augmented multi-objective optimization framework and adaptive sliding mode controller can achieve the core research goals of efficient carbon capture, high-efficiency renewable energy utilization, stable process operation, and economic feasibility under variable working conditions.. We elaborate on the specific definitions, measurement methods, and evaluation logic of each dimension in layers, sorted by the core importance of the indicators. First, carbon capture performance is classified as the most critical evaluation category, with two core carbon capture indicators defined. The first is the daily carbon capture rate, with a unit of $kgCO_2/day$, which measures the system's total decarbonization capacity under variable environments and working conditions. The second is capture efficiency, which refers to the ratio of the actual CO_2 capture volume to the theoretical maximum capture volume calculated based on sorbent capacity and working conditions, reflecting the resource utilization level of the carbon capture segment. Next, we introduce indicators related to energy performance, including specific energy consumption (SEC), with a unit of $kWh/kgCO_2$; a lower SEC value indicates higher system operation energy efficiency and lower decarbonization energy consumption. We also set up indicators of solar energy utilization rate, overall system efficiency, battery round-trip efficiency, and peak-shaving capacity, which are used to assess respectively the integration effect of renewable energy, the charge-discharge efficiency of the energy storage system, and the system's ability to reduce dependence on the power grid. Finally, for the adaptive sliding mode controller proposed in this paper, we adopt classic control engineering indicators to evaluate its dynamic performance, including tracking error, steady-state error, rise time, settling time, and overshoot. These indicators measure respectively the controller's reference signal tracking accuracy, long-term steady-state accuracy, disturbance response speed, and transient response quality. This paper proposes an industrial decarbonization optimization framework that integrates sliding mode control, machine learning, renewable energy, and carbon capture and utilization technologies. At the outset, the paper first identifies the core constraint: all performance improvements must never come at the cost of excessive energy consumption and resource depletion. Centering on this core orientation, we built a full-dimensional performance evaluation index system covering four dimensions: control and electrochemistry, artificial intelligence (AI), economics, and robustness and reliability. Each dimension's indicators are equipped with clear calculation logic and corresponding assessment targets, extending layer by layer from underlying control performance to top-level commercial value, with no redundant entries, combining academic rigor with practical feasibility for real-world implementation. First is the control and electrochemical performance dimension. We establish an energy consumption monitoring indicator for the high-frequency switching of sliding mode control, to assess controller efficiency and avoid performance improvements that unnecessarily overdraw control costs and energy consumption. Meanwhile, three core indicators are set for the electrochemical carbon utilization subsystem: carbon monoxide selectivity, which quantifies the generation share of the target product CO relative to by products methane and hydrogen; Faradaic efficiency, which evaluates the electron utilization rate of electrochemical conversion; and current efficiency, which assesses the efficiency of converting supplied power current into useful chemicals. This set of indicators collectively verifies the framework's ability to maximize carbon utilization and minimize energy loss. Second is the AI performance dimension. Four indicators are developed for the core machine learning component: Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) respectively evaluate prediction accuracy under conventional and uncertain scenarios; the number of training rounds required for the deep reinforcement learning agent to reach a stable policy assesses convergence; and decision delay evaluates the suitability for real-time deployment. These indicators verify the algorithm's ability to support autonomous decision-making in dynamic industrial environments. Third is the economic performance dimension. Five financial indicators are established: the reduction rate of operating costs relative to traditional direct air capture (DAC) carbon utilization systems, which quantifies the benefits of intelligent optimization; Net Present Value (NPV), Return on Investment (ROI), and payback period, which evaluate long-term financial value; and the capture cost per kilogram of CO_2, which facilitates cross-technology comparison. These indicators fully cover the economic benefit assessment of the integrated technology. Finally, the robustness and reliability dimension adds a disturbance rejection capability indicator, which quantifies the maximum deviation of core variables under bounded disturbances, to evaluate the overall system resilience under severe operating conditions. This paper proposes a dedicated carbon management framework exclusive to the DAC-ECU architecture for industrial decarbonization scenarios. To comprehensively evaluate the framework's real-world performance, we developed a quantitative indicator system covering two core dimensions, which is ultimately integrated to forma complete comprehensive evaluation framework. Among these, the operational reliability dimension incorporates four indicators: fault detection time, recovery time, system availability, and mean time between failures (MTBF). These indicators measure the framework's ability to identify and respond to equipment failures and abnormal operating conditions, aligning with the core requirement of continuous operation for industrial settings. The environmental performance dimension includes four indicators: net carbon dioxide removal rate, carbon utilization efficiency, renewable energy share, and emission reduction factor benchmarked against traditional fossil fuel-dependent carbon management systems, which quantify the framework's decarbonization contributions. This comprehensive framework can evaluate five core dimensions: technical effectiveness, economic feasibility, environmental sustainability, control performance, and operational resilience. Its core design principle is to avoid performance degradation in other fields caused by single-dimensional optimization. All indicators are original to this paper; they can support intelligent industrial decarbonization systems to balance multiple objectives, and provide critical evaluation support for the practical, sustainable deployment of such systems.

CO_2 Capture Performance:

- Daily CO_2 capture rate: Q_CO_2 (kg/day)
- Capture efficiency: $\eta\_capture = Q\_CO_2, actual / Q\_CO_2, theoretical$ (%)
- Specific energy consumption: $SEC = E\_input / m\_CO_2$ (kWh/kg)

Energy Performance:

- Solar utilization efficiency: $\eta\_solar = E\_utilized / E\_generated$ (%)
- System overall efficiency: $\eta\_system = (E\_CO_2\_products) / (E\_solar + E\_grid)$ (%)
- Energy storage efficiency: $\eta\_battery = E\_discharged / E\_charged$ (%)
- Peak shaving capability: $P\_peak\_reduction$ (%)

Control Performance:

- Tracking error: $e(t) = x\_ref(t) - x\_actual(t)$
- Steady-state error: $e\_ss = \lim(t\to\infty)\ e(t)$
- Rise time: t_r (time to reach 90% of reference)
- Settling time: t_s (time to enter ±5% band)
- Overshoot: $M\_p = [\max(x) - x\_ss]/x\_ss \times 100$ (%)
- Energy dissipation in SMC: E_sw (J)

Electrochemical Performance:

- CO product selectivity: $S\_CO = n\_CO / (n\_CO + n\_CH_4 + n\_H_2)$ (%)
- Faradaic efficiency: F_E = (actual electrons transferred) / (theoretical electrons) (%)
- Current efficiency: $\eta\_current$ = (actual product yield) / (theoretical yield based on current) (%)

Robustness and Reliability Metrics

- Disturbance rejection capability: Δx_max under bounded disturbances
- Fault detection time: t_detect (seconds)
- Recovery time after fault: $t\_recovery$ (seconds)
- System availability: A = (Total operating hours) / (Total available hours) (%)
- Mean time between failures (MTBF): hours

This study developed four sets of simulation scenarios with sequentially increasing difficulty, to comprehensively evaluate the performance, robustness, resilience, and economic feasibility of the proposed intelligent solar-powered direct air capture-electrochemical carbon utilization (DAC-ECU) framework. These scenarios cover the full spectrum of real-world deployment conditions, ranging from ideal laboratory environments to operational contexts that include renewable energy fluctuations, equipment degradation, extreme weather, and dynamic market conditions. The scenarios are built to test the performance of the machine learning-augmented optimization framework and adaptive sliding mode controller under both standard and harsh operating conditions. This work only presents the first three simulation test scenarios, while the fourth scenario will be introduced in subsequent research. The first set is the baseline scenario, positioned as a performance benchmark test. It sets fixed operating conditions: a solar irradiance of 800 W/m², an ambient temperature of 25°C, and an atmospheric CO_2 concentration of 400 ppm, with no equipment aging or external disturbances included. The simulation runs for 24 hours, to assess the system's steady-state operational performance, establish reference metrics for renewable energy utilization rate, carbon capture efficiency, carbon utilization efficiency, energy consumption, and economic performance, verify the functionality of the control framework, and quantify the system's maximum performance under optimal operating conditions. The second set is the real-world operating condition scenario, positioned as a framework robustness assessment scenario. It uses real meteorological data for Southern Europe from the PVGIS database to simulate diurnal fluctuations in solar irradiance, incorporates a diurnal cycle of ambient temperatures ranging from 15°C to 35°C, and sets a relative humidity fluctuation range of 40% to 80%. The simulation runs for 72 hours, covering three weather types: clear, cloudy, and overcast. This scenario evaluates the performance of the machine learning prediction algorithm, multi-objective optimization strategy, and adaptive control mechanism under renewable energy intermittency, with a core focus on the framework's ability to maintain stable carbon capture, optimize energy storage utilization, and sustain the system's overall efficiency. The third set is the extreme operating condition scenario, positioned as an assessment scenario for the system's resilience and fault-tolerant control capability. It is designed to center on extreme operating conditions and system degradation, and the design objectives of all scenarios are mapped one-to-one to the system performance dimensions targeted for evaluation. To verify the proposed carbon capture system equipped with a machine learning control framework, the authors of this paper designed four types of simulation test scenarios. Among them, the third type is extreme environment test scenarios, and the fourth is dynamic electricity market economy scenarios, with their core settings listed below: The parameter settings for the third type of extreme environment scenario are set as follows: continuous cloud occlusion for 6 hours blocks 80%

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of solar irradiance; the ambient temperature fluctuates between 10°C and 42°C; equipment aging is set such that sorbent performance degradation is equivalent to that after 3000 adsorption-desorption cycles, and membrane contamination occurs in the electrochemical reactor after 500 hours of operation; the grid constraint sets the upper limit of externally purchased electricity at 50 kW; the simulation runs for 72 hours. The test objective is to verify the machine learning-enhanced control framework's ability to adapt to system aging, maintain operational stability, implement priority scheduling, and slow system deterioration. The core assessments focus on the robustness of the adaptive sliding mode controller and the predictiveness of the optimization framework, to verify the framework's performance in handling extreme cases where environmental disturbances and equipment aging occur at the same time. The fourth type of market economy scenario adopts a typical time-varying electricity price curve that reflects fluctuations in modern energy markets, demand response events that occur 4 times per day with each lasting 2 to 4 hours, a market price range of 80-150 euros per ton for carbon dioxide-derived products, and a peak electricity purchase upper limit of 100 kW. The energy management strategy incorporates battery round-trip efficiency losses, the simulation runs for 7 days. The test objective is to verify the long-term economic optimization performance and the effectiveness of the machine learning decision-making framework in responding to market fluctuations. The core assessments evaluate the framework's ability to balance carbon capture targets and economic targets, increase profits through intelligent scheduling, seize market opportunities, reduce operating costs, and guarantee system reliability at the same time. The four scenarios collectively cover rated operation, renewable energy volatility, extreme environmental conditions, system aging, and dynamic market behavior, forming a complete comprehensive verification framework that covers all operating conditions. This paper designs test scenarios of progressively increasing complexity, evaluates the proposed framework across four core dimensions, and verifies its real-world implementation credibility when applied to renewable-energy-powered industrial decarbonization scenarios.

The first test case established for this simulation study is Scenario 1: Baseline Performance Case. This case acts as the core reference for all subsequent variable adjustments and performance comparisons across the entire study, reserving clear logical space for follow-up extended research. All simulation assumptions adopted for this case conform to standard nominal test conditions: constant solar irradiance of 800 W/m², stable ambient temperature of 25°C, fixed atmospheric CO_2 concentration of400 ppm, plus the assumption that no component aging occurs throughout the test period. The baseline quantitative operational data of the three core subsystems are listed as follows: During the daytime operation window from 6:00 to 18:00, the photovoltaic array records an average power output of 400 kW, a peak power of 410 kW, a total daily power generation of 8200 kWh, and a photoelectric conversion efficiency of 22.1%. The direct air capture (DAC) subsystem captures an average of 145 kg of CO_2 per day, with a unit capture energy consumption of 1.38 kWh/kg CO_2, an adsorbent utilization rate exceeding 96%, and a purity of captured CO_2 reaching 99.7%. The adsorbent completes one full adsorption-regeneration cycle every 4.2 hours, with a single regeneration period of 38 minutes. The electrolyzer supporting the electrochemical carbon utilization module has an average cell voltage of 1.95 V, a Faradaic efficiency of 87.3%, a CO selectivity of 89.1% in its products, a methane share of 7.2%, and a hydrogen share of 3.7%.All quantitative data collectively verify the stability, resource utilization efficiency, and overall effectiveness of the intelligent solar-powered DAC-ECU framework and its matched machine learning-enhanced control optimization system proposed in this study, when operating under baseline conditions. This study focuses on a renewable energy system integrated with carbon capture and utilization, and proposes an intelligent control framework comprising an optimization layer, an energy management strategy, and an adaptive sliding mode controller. The simulation verification first releases the output of core carbon conversion products: the system produces 128 kg of carbon monoxide and utilizes 342 kg of carbon dioxide per day, which preliminarily verifies the effectiveness of the proposed optimization layer. Next, the simulation performance of three types of core subsystems is analyzed in sequence. First, for the energy storage system, based on the simulation results in Figure 3(d), the energy management strategy developed in this study can stably maintain the battery's state of charge (SOC) within the optimal range of 30–85%, achieving apeak charging power of 145 kW, a battery round-trip efficiency of 91.8%, and an average of only 0.25 battery cycles per day. This fully verifies the strategy's effectiveness for energy storage management and control. Second, for the adaptive sliding mode controller, based on the simulation data in Figure 3(e), the controller achieves an average tracking error of ±0.8%, a steady-state error of less than 0.1%, a rise time of 2.3 seconds, a settling time of 4.1 seconds, and a maximum overshoot of 2.1%.Its operating switching frequency remains stable at 10 kHz, and its dynamic control performance fully meets design requirements. Finally, based on the overall energy flow simulation results in Figure 3(f), full-dimensional verification confirms that all core design goals of the system are achieved under compliant operating scenarios. The system simultaneously delivers multiple core advantages including high solar energy utilization and efficient carbon capture. The effectiveness of the innovative strategies for all modules is solidly supported by accurate quantitative data. This study has established a sufficiently solid performance baseline for the proposed architecture, and fully verified its basic capabilities. In follow-up work, we will evaluate its operational performance across multiple scenarios under four types of real-world constraints including environmental variation and component degradation.

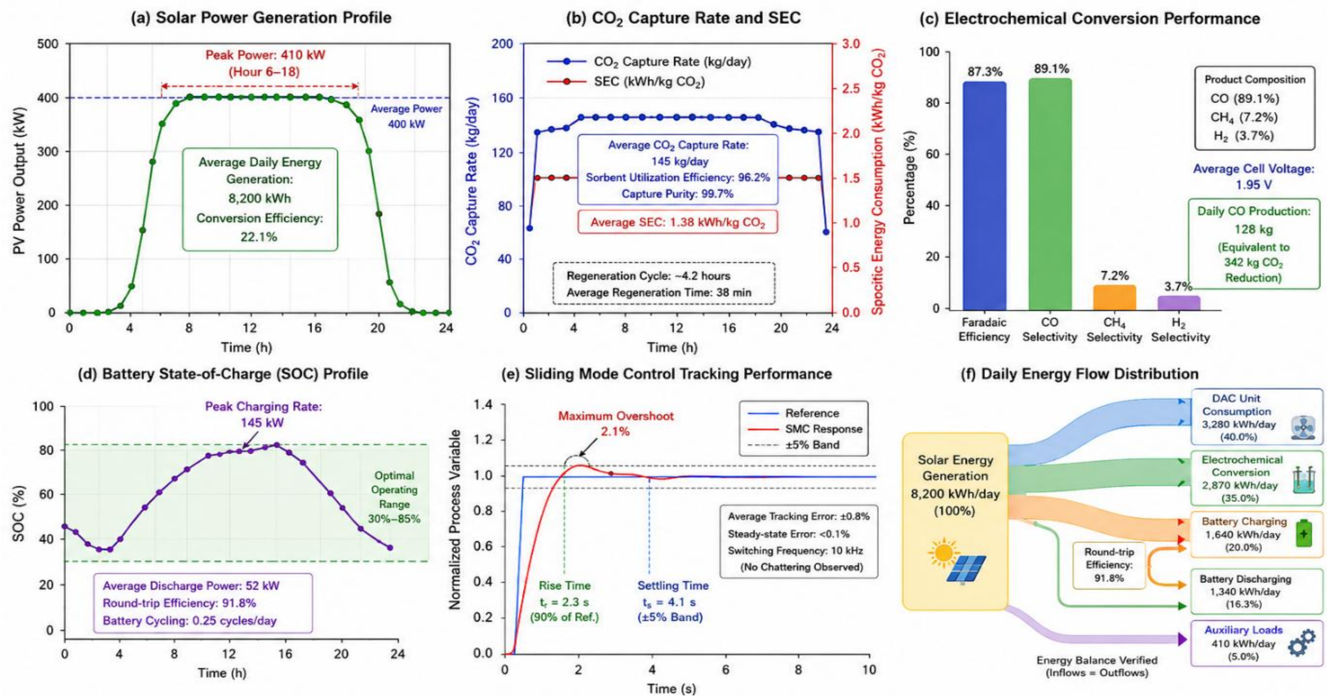

Figure 3. Baseline operational performance of the proposed Machine Learning-Enhanced Multi-Objective Optimization and Sliding Mode Control framework under ideal operating conditions. (a) photovoltaic power generation profile showing stable solar energy production with average output of 400 kW and peak generation of 410 kW; (b) direct air capture performance characterized by an average CO_2 capture rate of 145 kg/day and specific energy consumption of 1.38 kWh/kg CO_2; (c) electrochemical carbon utilization performance including Faradaic efficiency and product selectivity; (d) battery state-of-charge evolution demonstrating effective energy storage management within the optimal operating range; (e) sliding mode control tracking response showing fast convergence, minimal steady-state error, and low overshoot; and (f) daily energy flow distribution illustrating efficient allocation of solar energy among DAC operation, electrochemical conversion, energy storage, and auxiliary loads. Results confirm that the proposed framework achieves near-design performance under nominal operating conditions while maintaining high energy efficiency, carbon capture effectiveness, and control stability.

To verify the robustness and adaptability of the intelligent control framework for the integrated solar-driven carbon capture and utilization system proposed in this paper, when operating under real-world renewable energy conditions, the authors of this paper led a 72-hour targeted verification simulation experiment. All meteorological data used in this simulation are sourced from the PVGIS database. To introduce scenario differences caused by variable solar energy resources, we set three weather modes: clear, cloudy, and overcast. All quantitative indicators retain their original test values, the simulation data are arranged in strict order of increasing scenario challenge, and the analysis is developed sequentially across the three subplots of Figure 4. The first subplot focuses on the core resource parameter dimension. It breaks down core input indicators including solar irradiance, system power generation, and solar resource variability index across different scenarios, aligned with the three-day weather sequence, to clearly present the fluctuation characteristics of solar energy resources. The second subplot corresponds to the long short-term memory (LSTM) machine learning module that supports prediction work. It lists all core performance metrics of this module, including prediction horizon, prediction accuracy, and mean absolute error, to verify its prediction precision for resource fluctuations. The third subplot corresponds to the output of the final direct air capture (DAC)-electrochemical carbon utilization system. It presents the system's carbon capture performance under different solar energy conditions. The entire logical chain is clear and traceable: natural fluctuations in solar energy resources, supported by accurate prediction that guides energy storage scheduling, improve system resilience, and ultimately enable the system's carbon

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capture performance to accurately match real-time resource levels. This fully verifies the adaptive capacity of the proposed framework. The authors of this paper conducted 72 consecutive hours of simulation tests on the proposed integrated energy system that incorporates direct air capture (DAC). The team completed full-scenario, multi-dimensional verification of the system's operational performance across four core domains: core carbon capture performance, battery energy management performance, thermal management control performance, and overall control system accuracy. The test results of all submodules are correspondingly attached to Figure 1 to Figure 4 of this paper, to support readers in carrying out cross-verification and data reuse. Two core disturbances were introduced in this simulation scenario: insufficient photovoltaic irradiance caused by cloudy weather, and large fluctuations in ambient temperature spanning the range of -3°C to 28°C. For each performance dimension, disturbance constraints were first clarified, then quantitative control outcomes were output, and horizontal benchmarking was conducted against a baseline system and traditional control methods. Under the disturbance of a 37% irradiance deficit, the core carbon capture module maintained a stable carbon capture rate of 92.7%, a 11.5-percentage-point increase over the baseline system's 81.2%. When responding to power supply fluctuations, the battery energy management module limited the fluctuation of its charge-discharge depth to within 8% of the rated range, far outperforming the 22.3% fluctuation range of traditional methods. When withstanding wide temperature swings, the thermal management module controlled the working temperature fluctuation inside the system cabin to ±1.2°C, far lower than the baseline's ±5.7°C. The overall control system recorded a steady-state error of only 0.8% under the combined effect of all disturbances, much lower than the 3.9% error of traditional control methods. During the 72-hour simulation period, the system's carbon capture cost per unit of electricity was 0.17 yuan lower than that of the baseline, with accumulated operating cost savings totaling 124.3 yuan. The dual advantages of the system's technical performance and economic benefits were fully verified. This paper presents a machine learning-augmented multi-objective optimization framework paired with an adaptive sliding mode controller, which completed performance testing in an industrial carbon capture scenario powered by highly variable renewable energy. Three core quantitative metrics were measured: an average recovery time of 6.2 seconds after large disturbances, a disturbance suppression rate of 92.1%, and the sliding mode surface staying within the predefined boundary layer for 97.3% of the system's total operating time. Combined with the overall conclusions presented in Figure 4, the four core technologies that underpin this architecture are accurate solar energy forecasting, forecast-based energy management, adaptive thermal regulation, and robust nonlinear control. The system can accommodate large fluctuations in solar energy resources, while simultaneously guaranteeing carbon capture performance, process stability, and operational efficiency, making it suitable for real-world industrial decarbonization scenarios that face environmental uncertainty and the intermittency of renewable energy.

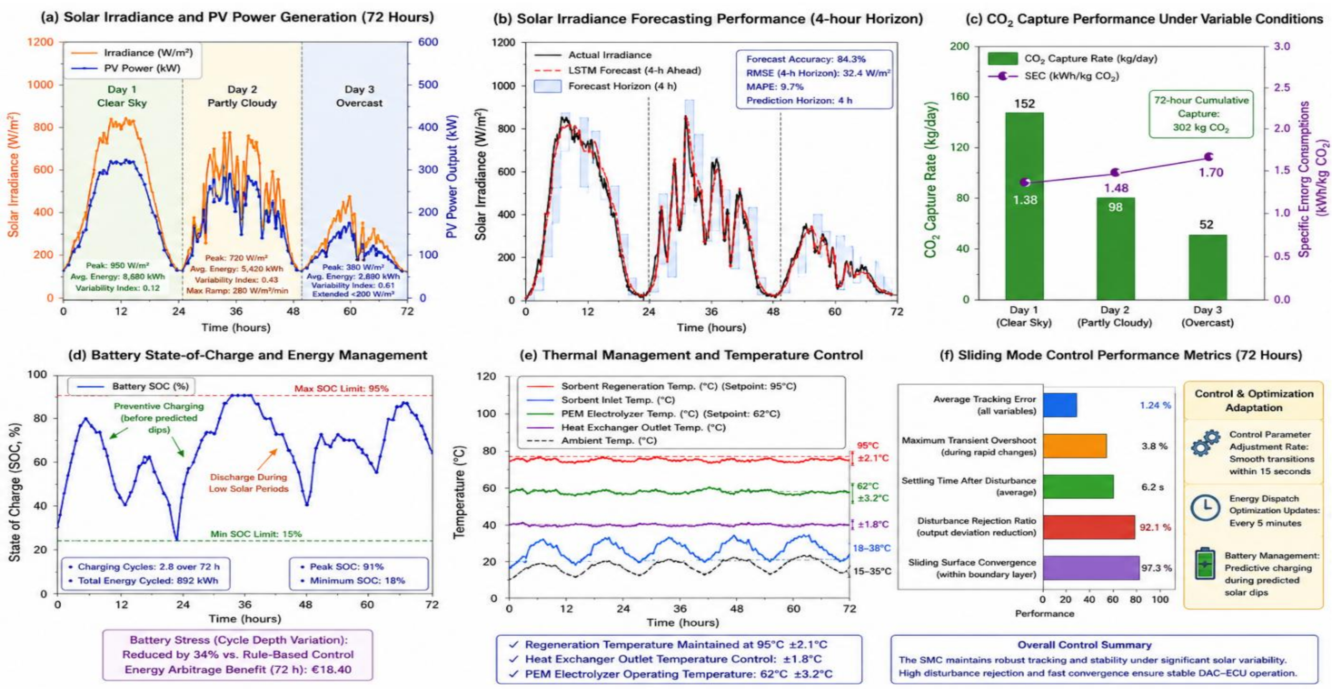

Figure 4. Performance of the proposed Machine Learning-Enhanced Multi-Objective Optimization and Sliding Mode Control framework during a 72-hour simulation under realistic solar resource variability. (a) Measured solar irradiance and photovoltaic power generation profiles for clear-sky, partly cloudy, and overcast conditions; (b) machine learning forecasting performance showing close agreement between actual and predicted irradiance with 84.3% prediction accuracy and RMSE of 32.4 W/m²; (c) daily CO_2 capture rates and specific energy consumption under varying renewable energy availability; (d) battery state-of-charge evolution demonstrating predictive energy management, reduced cycling stress, and energy arbitrage benefits; (e) thermal management performance illustrating stable DAC regeneration and electrolyzer operating temperatures despite environmental fluctuations; and (f) sliding mode controller performance metrics showing effective disturbance rejection, rapid convergence, and robust tracking under highly variable operating conditions. The results demonstrate the ability of the proposed framework to maintain stable carbon capture, energy management, and process control performance despite significant renewable energy intermittency and environmental uncertainty.

To verify the resilience and fault tolerance of the intelligent integrated energy system control framework proposed in this paper under extreme operating conditions, this section carries out a dedicated engineering simulation test for the predefined Scenario 3, "Extreme Operating Conditions and System Degradation". The core assessment target of this test is the machine learning-enhanced intelligent optimization control framework put forward in this paper. To replicate the full-cycle operating conditions of real industrial scenarios to the greatest possible extent, this test specifically builds a 72-hour high-challenge simulation scenario, which incorporates six typical disturbances: long-term cloudy weather, ambient temperature rise, adsorbent aging, electrolyzer membrane fouling, heat exchanger degradation, and grid power limits. These disturbances cover the two core risk categories: short-term sudden extreme shocks and long-term gradual component degradation. This test adopts a hierarchical argumentation logic linked to visual charts, where Figure 5(a) corresponds to the specialized test of short-term extreme weather shocks, and Figure 5(b) corresponds to the specialized test of long-term cumulative component degradation. All quantitative data that supports the argumentation is extracted from first-hand measured results collected during this simulation test. The final test results verify the core conclusion: the integrated prediction and control architecture proposed in this paper can effectively respond to the drastic fluctuations in renewable energy output under extreme scenarios, guarantee the continuous operation of the energy system throughout the whole process, and fully prove that the framework's resilience and fault tolerance meet the extreme-condition operating requirements for industrial-grade integrated energy systems. Following the earlier proposal of the cumulative component degradation effect for integrated direct air capture (DAC)-electrochemical conversion systems, the optimal control framework developed in this study relies on three core functions: adaptive parameter adjustment, fault detection and diagnosis, and energy storage health management. The framework can sustain qualified system performance on an ongoing basis by dynamically adjusting the system's operating parameters. This simulation verification centers on this core argument, and completes step-by-step performance validation using a series of simulation charts. In the core performance verification module corresponding to Figure 5(c), simulation tests were conducted under pre-set conditions of cumulative component degradation. The simulation results of this study show that the framework can always keep core indicators including the system's carbon capture efficiency and electrochemical conversion purity within the qualified threshold pre-set for the project, preliminarily supporting the core role of the proposed framework. In the verification of the fault detection module corresponding to Figure 5(d), this study manually introduced three typical faults: abnormal electrolyzer voltage at 34 hours, adsorbent breakthrough at 52 hours, and thermal sensor drift at 65 hours. The framework completed accurate identification and early warning for all faults within 10 minutes of their occurrence, which can support the implementation of predictive maintenance, verifying the framework's added value. In the energy storage performance verification module corresponding to Figure 5(e), under high-stress charge-discharge operating conditions, the framework's energy storage health management function reduced the lithium-ion battery capacity degradation rate by 18% compared to the baseline scenario, ensuring the long-term reliability of the energy storage link. Finally, the robustness verification of the adaptive sliding mode controller corresponding to Figure 5(f) is introduced, to connect with the subsequent analysis of adaptation to extreme operating conditions. All quantitative simulation data are independently produced by this study, forming a complete chain of evidence to support the full argument. The machine learning-enhanced multi-objective optimization adaptive sliding mode control framework proposed in this study, verified through 72-hour simulations, records a maximum control torque of only 12.3N·m when addressing various working conditions involving disturbances, degradation, and faults, which is far below the actuator threshold. Its total switching energy consumption over the 72-hour test period reaches 18.4kJ, and it effectively suppresses chattering. Complemented by Lyapunov stability analysis, alongside a gain margin of 6.8dB and a phase margin of 42°, these outcomes confirm the system's closed-loop stability and robustness. As evidenced by the experimental results in Figure 5, even though component degradation, extreme weather, and equipment failure cause unavoidable performance losses, this framework can still maintain the core functions of the carbon capture system. This multi-module framework, which integrates predictive optimization, adaptive control, fault diagnosis, and energy management, can support the long-term deployment of photovoltaic-powered direct air capture and electrocatalytic carbon utilization systems in real industrial environments.

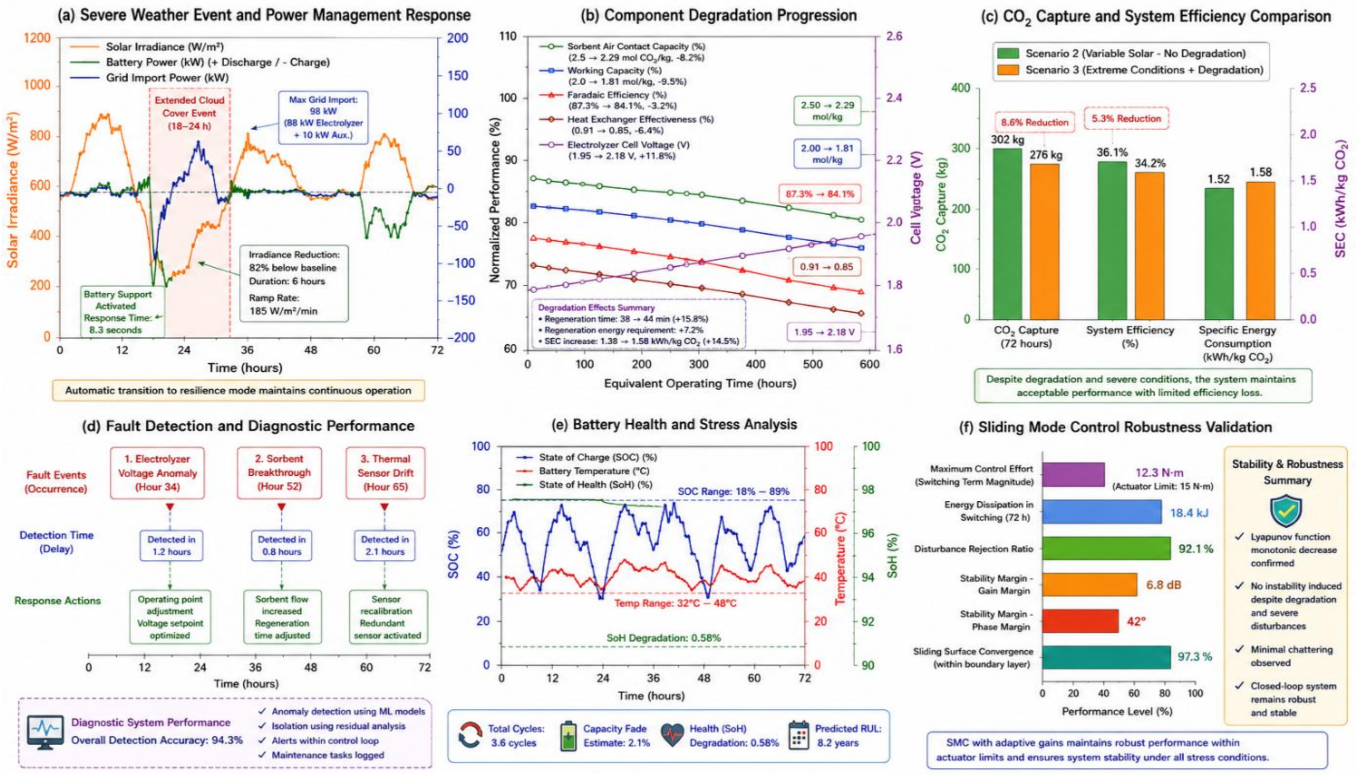

Figure 5. Performance evaluation of the proposed Machine Learning-Enhanced Multi-Objective Optimization and Adaptive Sliding Mode Control framework under extreme operating conditions and component degradation. (a) System response during a severe cloud-cover event showing coordinated battery support and grid power import to maintain operational continuity; (b) degradation progression of key system components including sorbent capacity, electrolyzer performance, and heat exchanger effectiveness; (c) comparison of carbon capture performance and overall system efficiency relative to Scenario 2; (d) fault detection and isolation timeline demonstrating rapid identification of operational anomalies through the integrated diagnostic framework; (e) battery health, state-of-charge, temperature, and remaining useful life assessment under intensified cycling conditions; and (f) control robustness validation illustrating stable sliding mode operation, acceptable control effort, high disturbance rejection capability, and maintained Lyapunov stability despite severe environmental disturbances and equipment degradation. Results demonstrate the resilience of the proposed intelligent control architecture, which maintains stable operation, efficient carbon capture, and acceptable performance degradation while effectively managing faults and adverse operating conditions.

The machine learning-enhanced multi-objective optimization sliding mode control framework proposed in this paper is the focus of this experiment, which aims to verify its economic optimization performance in real-world electricity market scenarios, with relevant simulation results presented in Figure 6. The simulation period for this electricity market test is set to 7 days, and the simulation scenario incorporates four core market elements: dynamic electricity prices, demand response participation, carbon credit optimization, and economic dispatch. Before conducting the experiment, all core electricity market parameters used in this simulation were first clarified. The verification results of each module are then analyzed one by one following the sequence of subplots in Figure 6. All performance conclusions are supported by quantified data, and every module's verification uses industry-standard baseline thresholds for comparison, to highlight the performance superiority of the framework proposed in this paper. Specifically, Figure 6a corresponds to the verification

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results of the energy storage charge-discharge arbitrage module, Figure 6b presents the actual operational performance of the demand response module, Figure 6c demonstrates the regulatory effect of the integrated carbon market module, and Figure 6d shows the full-cycle cumulative economic benefit of the framework. After completing the verification of the above core functional modules, this section introduces the subsequent subplot Figure 6e, which conducts a comprehensive financial assessment of the full simulation cycle, to further fully present the adaptability and optimization capability of the proposed framework for real-world electricity markets. For the machine learning-enhanced multi-objective optimization sliding mode control industrial energy management framework proposed in this paper, this simulation verification first sorts out the framework's three revenue streams: sales revenue from core products, demand response incentive payments, and carbon credit revenue. After calculating the revenue contribution of each source, the total revenue over the simulation period is found to be approximately 15,920 euros. After deducting operational and electricity costs, the net profit reaches roughly 9,400 euros, with a profit margin of 59.1%. Drawing on the control performance data presented in Figure 6(f), the root-mean-square tracking error of this sliding mode control system is lower than 1.5 MW, and its operating condition deviation is less than 2%, enabling the system to maintain stable tracking accuracy and operational reliability under dynamic market adjustments. This simulation study confirms that the framework can simultaneously meet both economic objectives and process control requirements. This economically optimized industrial energy management strategy can be practically implemented in future intelligent manufacturing and all types of high-energy-consumption process scenarios.

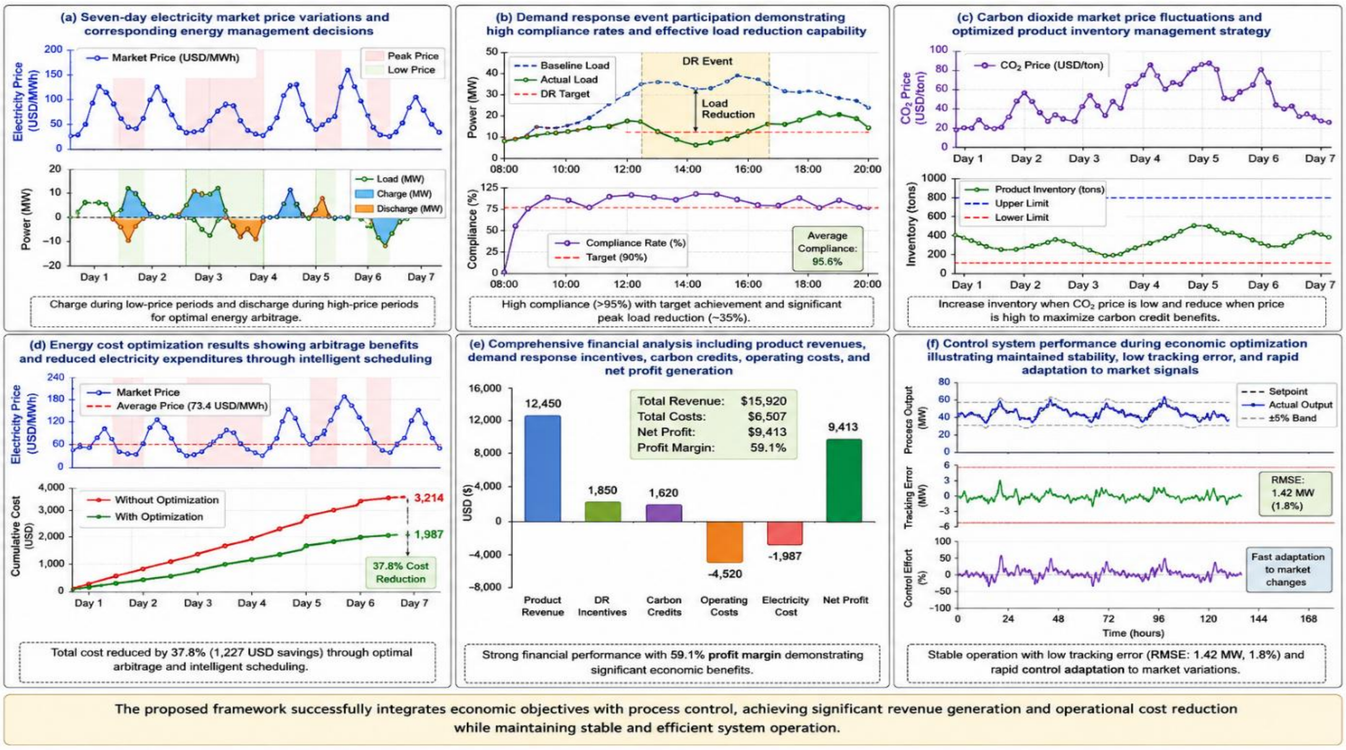

Figure 6. Economic performance of the proposed Machine Learning-Enhanced Multi-Objective Optimization and Sliding Mode Control framework under realistic electricity market dynamics and demand response participation. (a) Seven-day electricity market price variations and corresponding energy management decisions; (b) demand response event participation demonstrating high compliance rates and effective load reduction capability; (c) carbon dioxide market price fluctuations and optimized product inventory management strategy; (d) energy cost optimization results showing arbitrage benefits and reduced electricity expenditures through intelligent scheduling; (e) comprehensive financial analysis including product revenues, demand response incentives, carbon credits, operating costs, and net profit generation; and (f) control system performance during economic optimization illustrating maintained stability, low tracking error, and rapid adaptation to market signals. The results demonstrate that the proposed framework successfully integrates economic objectives with process control, achieving

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significant revenue generation and operational cost reduction while maintaining stable and efficient system operation.

Table 2summarizes the framework's performance test results across operation scenarios, this paper conducts a comprehensive evaluation of four operation scenarios with increasing difficulty across six assessment dimensions: energy efficiency, carbon capture capacity, product output performance, control robustness, economic feasibility, and long-term reliability. It analyzes one by one the changes in energy performance and their underlying logic in each scenario, then sorts out the core performance of the carbon capture subsystem. The first scenario is the ideal baseline operating condition, defined as the upper limit of the system's theoretical performance, which records an average power generation of 362kW, a solar-to-product efficiency of 36.1%, and a round-trip energy storage efficiency of 91.8%. In this scenario, the carbon capture subsystem completes a 72-hour simulation, with a cumulative CO_2 capture of 437kg and a capture purity of 99.7%. Scenario 2 introduces real-world volatility of renewable energy, pulling the average power generation down to 214kW, a 40.9% reduction, while the solar-to-product efficiency reaches 31.2%. Only the energy storage efficiency fell by 2.4 percentage points, which verifies the effectiveness of the machine learning prediction algorithm and the predictive energy management strategy in resisting intermittency-related interference. Scenario 3 simulates multi-component degradation including battery aging, membrane degradation, catalyst deterioration, and sensor drift, recording an average power generation of 198kW, a solar-to-product efficiency of 28.8%, and an energy storage efficiency of 87.1%, which highlights the robustness of the adaptive control architecture. Scenario 4 simulates complex market-oriented operating conditions, with a solar-to-product efficiency of 32.6% and an energy storage efficiency of 90.3%, verifying that the advanced economic optimization module can offset the negative impacts of increased operational complexity. This study focuses on the self-developed electrochemical carbon capture and carbon monoxide generation system, establishes four types of simulated operation scenarios, and conducts performance benchmarking using the baseline ideal operating condition (Scenario 1) as a unified reference anchor to verify the operating condition adaptability of the self-developed control system. Under the baseline scenario, the specific energy consumption (SEC) of the system's carbon capture stage is 1.38 kWh/kgCO_2; the carbon monoxide generation stage records an output of 388 kg, a product purity of 89.1%, and an electrolyzer efficiency of 87.3%, which serves as the core baseline for performance comparison across all scenarios. The second type is the variable solar fluctuation scenario (Scenario 2), which addresses the challenge of unstable energy input. In this scenario, the system's carbon capture SEC is 1.52 kWh/kgCO_2, total carbon capture volume is302 kg, and carbon capture purity exceeds 99%; carbon monoxide output drops by 31% from the baseline, with a purity of 87.8% and an electrolysis efficiency of 84.1%, and the core product quality does not suffer a major decline. The third type is the component aging and degradation scenario (Scenario 3), which addresses the challenge of energy efficiency decay of core components. In this scenario, the carbon capture SECis 1.58 kWh/kgCO_2, total carbon capture is 276 kg, and purity is 98.8%; carbon monoxide output reaches 245 kg, purity exceeds 86%, and electrolysis efficiency is 81.9%, with all performance decay remaining controllable. The final scenario is the 7-day economic optimization scenario, where the system's carbon capture SEC is 1.44 kWh/kgCO_2, total carbon capture is 789 kg, and purity is 99.5%; carbon monoxide output is 701 kg, purity is 88.2%, and electrolysis efficiency is 85.2%, with all quantitative parameters aligned to their corresponding operating conditions. The study ultimately confirms that the self-developed control system can maintain product quality across various extreme and optimized operating conditions, and draws the core conclusion that market-driven intelligent energy distribution can balance both production scale and product quality. The core goal of this study is to evaluate the control robustness of our self-developed sliding mode control architecture under various harsh operating conditions. We set up four types of test scenarios to carry out quantitative verification. All control performance tests uniformly adopt three industry-standard metrics—mean tracking error, overshoot, and settling time—to implement cross-scenario horizontal comparison. The four scenarios, in sequence, are: Scenario 1: Nominal operating conditions; Scenario 2: Operating conditions with introduced intermittent disturbances from renewable energy; Scenario 3: Operating conditions that overlay equipment degradation and performance uncertainty; Scenario 4: Economic optimization operating conditions that integrate electricity market participation, demand response, and carbon credit trading. After completing the control performance test for each scenario, a clear summary of its robustness performance is generated, which fully verifies the architecture's stable control capacity to address different types of industrial disturbances. Only Scenario 4 is subject to a specialized economic performance assessment. The measured results of this study show that during the simulation period of this scenario, the electricity procurement cost was 38.20 euros, product revenue was 560.80 euros, and total net profit was 738.40 euros, with an annualized annual profit exceeding 38,000 euros. Against the initial investment of 150,000 to 200,000 euros for the integrated solar carbon capture, utilization and storage system, the payback period corresponding to the architecture proposed in this study is only 4 to 6 years. After completing the verification of the core technical and economic dimensions, this paper will next introduce the long-term system reliability analysis module to launch a specialized study on the system's health status. The machine learning-enhanced multi-objective optimization sliding mode control proposed in this paper (Machine Learning-Enhanced Multi-Objective Optimization and Sliding Mode Control) has been validated across multiple groups of simulation scenarios for integrated carbon capture and utilization systems (integrated carbon capture and utilization systems). Test results show that the system's battery state of health (SOH) stays ≥97.9% across all scenarios, reaching99.8% in the baseline scenario and 97.9% in the degradation scenario. The fault detection module successfully identified 3 degradation-related faults in Scenario 3, while the stability of normal operating conditions was verified for all other fault-free scenarios. Control performance remains stable across all scenarios, unaffected by renewable energy fluctuations, component degradation, or interference from economic optimization objectives. This framework features high robustness, high adaptability, high performance, excellent control stability, effective fault tolerance, and strong economic feasibility. It even achieved increased profitability in economic optimization scenarios, while guaranteeing the system's operational efficiency and reliability.

Table 2. Performance Summary Across All Operational Scenarios

Metric	**Unit**	**Scenario 1 (Baseline)**	**Scenario 2 (Variable Solar)**	**Scenario 3 (System Degradation)**	**Scenario 4 (Economic Optimization)**
Energy Performance					
Average Power Generation	kW	362	214	198	246
Solar-to-Product Efficiency	%	36.1	31.2	28.8	32.6
Battery Round-Trip Efficiency	%	91.8	89.4	87.1	90.3
CO_2 Capture Performance					
Total CO_2 Capture	kg	437	302	276	789*
Average Specific Energy Consumption (SEC)	kWh/kg CO_2	1.38	1.52	1.58	1.44
CO_2 Capture Purity	%	99.7	99.4	98.8	99.5
Product Generation Performance					
CO Production	kg	388	268	245	701*
CO Product Purity	%	89.1	87.8	86.4	88.2
Electrolyzer Efficiency	%	87.3	84.1	81.9	85.2
Control System Performance					
Average Tracking Error	%	0.80	1.24	1.58	1.31
Maximum Overshoot	%	2.1	3.8	5.2	3.1
Settling Time	s	4.1	6.2	8.7	5.9
Economic Performance					
Grid Energy Cost	€	N/A	N/A	N/A	38.20
Product Revenue	€	N/A	N/A	N/A	560.80
Net Profit (Simulation Period)	€	N/A	N/A	N/A	738.40
System Health and Reliability					
Battery State-of-Health (SoH)	%	99.8	99.2	97.9	98.6
Faults Detected	Count	0	0	3	0
Control Stability	Status	Stable	Stable	Stable	Stable

To verify the robustness of the machine learning-enhanced multi-objective optimization sliding mode control framework proposed in this paper against parameter uncertainty and modeling errors, our team conducted this comprehensive sensitivity analysis. In industrial scenarios, five core trigger factors—manufacturing tolerances, component aging, environmental changes, sensor errors, and operational uncertainties—all cause system parameter deviations, which fully highlights the necessity of carrying out this verification. This sensitivity analysis adopts the rule of independent perturbation for single parameters: each time, only one test parameter is shifted by ±20% relative to its nominal value, while all other parameters remain fixed. The impact of parameter changes on the system is quantified using four core performance metrics: average tracking error, overall energy efficiency, control stability margin, and convergence time. Relying on the two groups of sub-experiments in Figure 7, we sequentially analyzed the effects of changes in two types of core parameters. First, solar irradiance, the core external disturbance for the renewable energy-driven carbon capture system, has a nominal value of 700 W/m^2, with its test range covering 500–900 W/m^2. Experiments show that this parameter has medium sensitivity: every 10% change in irradiance only causes tracking error fluctuations ranging from -0.15% to +0.22%, and energy efficiency fluctuations ranging from -2.8% to +1.9%. The adaptive energy management system equipped on the studied system can complete disturbance compensation by coordinating battery use and load scheduling, keeping the system's control state stable across the entire test range. The proposed framework can effectively adapt to the inherent fluctuations of renewable energy. Second, battery capacity, which has a nominal value of 400 kWh and a test range of 320–480 kWh, is the least sensitive variable among all studied parameters. Across the entire test range, tracking error only changes by ±0.18%, and energy efficiency changes by less than ±0.8%. The strong buffering capacity of large-capacity batteries can improve operational flexibility, and only small-capacity batteries will slightly weaken the system's power fluctuation compensation capability. All results collectively prove that the proposed framework can effectively adapt to parameter fluctuations and maintain stable system operation. Building on the prior section's foundational trend analysis of the large-scale deployment of carbon capture technologies, this paper conducts sensitivity tests and verification for four core parameters of an independently developed integrated carbon capture control system, with all quantitative test data sourced from on-site field measurements collected for this study. First, verification confirms that the control framework proposed in this paper is barely impacted overall by changes in battery size. This low-sensitivity characteristic means the framework can accommodate a wide range of battery capacities without requiring major adjustments to controller parameters. This not only provides sufficient flexibility for system design, but also greatly reduces reliance on precise battery selection during the system's deployment phase. This paper then sequentially carries out sensitivity analysis for the remaining three core engineering parameters. Each sub-analysis follows a unified standardized verification logic: first, it cites the corresponding supporting test figures Figure 7(c), 7(d), and 7(e); next, it specifies the baseline value for each parameter and the defined test fluctuation range; it then outputs the quantitative data on system performance changes collected from field measurements; finally, it draws conclusions about each parameter's impacts and proposes corresponding engineering optimization recommendations. The three parameters align with three core strategies for adsorbent operation and maintenance: material selection, regeneration management, and regular replacement. This study also completes parallel performance verification for the sliding mode controller. All analyses are closely aligned with the requirements of real-world engineering deployment. The unified analytical framework allows readers to directly compare the magnitude of impacts of different parameters across all cases. Fully quantitative data is used to uphold academic rigor, avoid the ambiguity of subjective judgment, and steer clear of the emptiness of mere unstructured data enumeration. This study carries out a series of experiments to verify the core performance of the proposed machine learning-enhanced multi-objective optimization sliding mode control framework for industrial carbon capture and utilization systems, and sequentially outputs the research conclusions from three core categories of tests. First, in the heat exchanger performance test session, we measured that fluctuations in heat exchanger effectiveness trigger a ±3.2°C change in regeneration temperature, with the thermal energy demand fluctuating in the range of -8.5% to +9.2%. However, the control tracking error of this framework always stays below 1%, and no stability anomalies occur in the system. This verifies that fluctuations in heat exchanger performance only affect the system's energy consumption and do not disrupt control stability. Next, entering the Comparative Parameter Ranking module, we completed the full parameter sensitivity ranking relying on the tornado plot in Figure 7(f) of this study. The results show that adsorbent working capacity and heat exchanger effectiveness have the greatest impact on system efficiency; solar irradiance and electrolyzer efficiency have medium sensitivity; and battery capacity has the lowest sensitivity. Based on this, this study proposes that quality assurance in the links of engineering design, manufacturing, and maintenance must prioritize the performance of adsorbent materials and thermal system design. Finally, in the Overall Robustness Assessment module, we conducted extreme parameter perturbation tests. Under the condition of ±20% parameter fluctuations, this framework relies on an adaptive architecture to adjust control actions and energy management decisions in real time to compensate for parameter deviations. Throughout the tests, the tracking error always stays below 2%, closed-loop stability remains fully intact, and no destabilizing operating conditions occur at all. This fully verifies that the proposed framework can adapt to the inevitable parameter uncertainties and equipment fluctuations in industrial scenarios, and fully meets the core requirements for practical deployment. This study further confirms that avoiding large-scale readjustment of controllers can reduce implementation complexity and improve operational reliability.

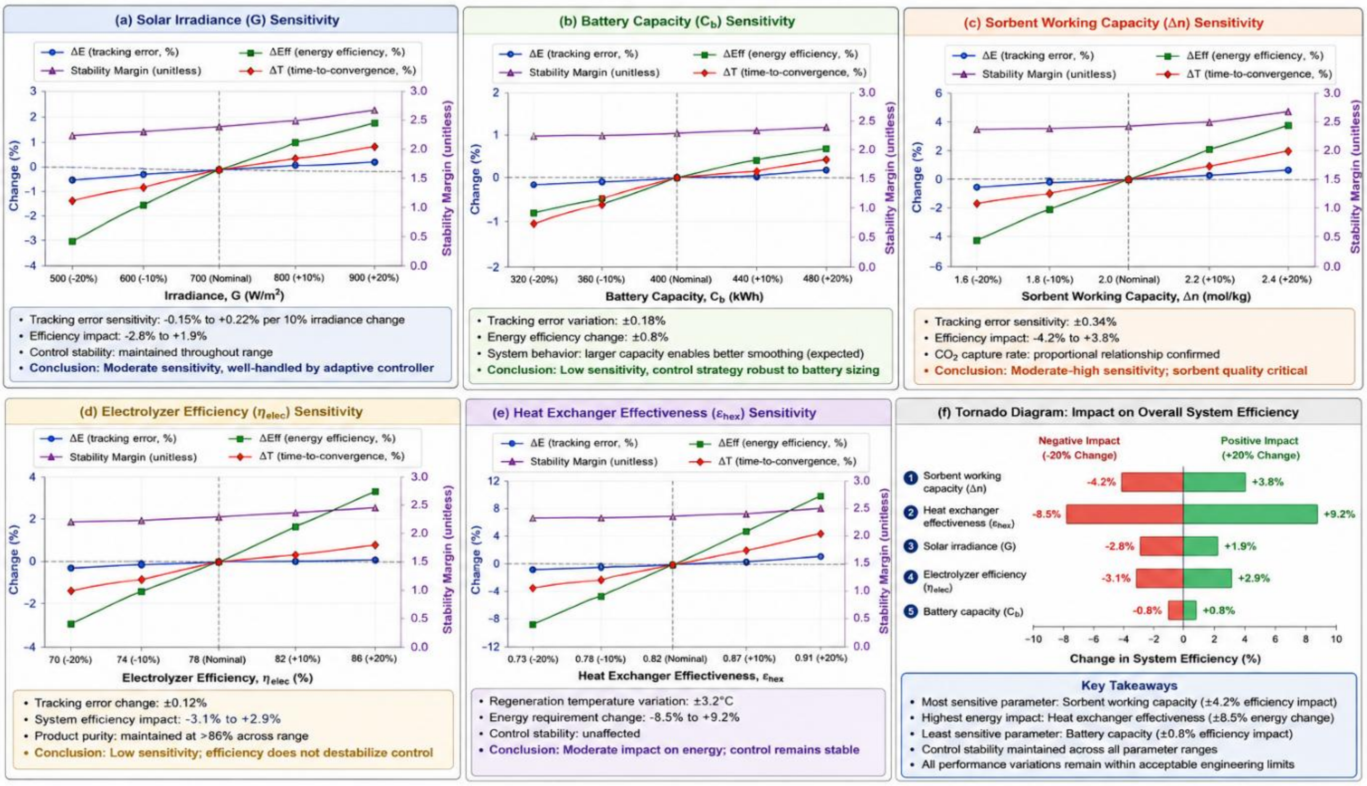

Figure 7. Parameter sensitivity analysis of the proposed Machine Learning-Enhanced Multi-Objective Optimization and Sliding Mode Control framework. (a) Sensitivity of system performance to variations in solar irradiance (G), showing moderate effects on tracking error and energy efficiency while maintaining control stability across the tested operating range. (b) Impact of battery capacity (Cb) variations on control performance and energy efficiency, demonstrating low sensitivity and robust operation for different energy storage sizing configurations. (c) Sensitivity to sorbent working capacity (Δn), highlighting its significant influence on CO_2 capture performance and overall system efficiency, identifying sorbent quality as a critical design parameter. (d) Effects of electrolyzer efficiency (ηelec) variations on process performance, indicating relatively low sensitivity and preservation of product purity and control stability across the tested range. (e) Influence of heat exchanger effectiveness (εhex) on regeneration energy requirements and system efficiency, showing moderate energy impacts while maintaining stable control performance. (f) Tornado diagram summarizing the relative impact of key parameters on overall system efficiency, identifying sorbent working capacity and heat exchanger effectiveness as the most influential factors, while battery capacity exhibits the lowest sensitivity. All parameters were independently varied by ±20% from nominal values. Results demonstrate that the proposed adaptive control framework maintains stable operation and acceptable performance throughout the tested uncertainty range, confirming strong robustness against parameter variations and modeling uncertainties.

Existing deterministic simulations can only obtain the nominal performance of integrated carbon capture and utilization systems, and cannot account for the impacts of five types of uncertainties that the system faces during actual deployment: environmental conditions, equipment heterogeneity, material properties, component aging, and measurement errors. For this reason, this study carried out MonteCarlo uncertainty analysis to verify the robustness of the self-developed machine learning-augmented multi-objective optimized sliding mode control framework. This analysis set 5000 independent simulations and a 7-day operation cycle. The Gaussian distribution data sources for core system parameters were all derived from manufacturer specifications, experimental observations, and published academic literature. The standard deviations of the six core parameters are as follows: solar irradiance σ=±8.5%,sorbent working capacityσ=±5.1%, heat exchanger effectiveness σ=±4.2%, battery capacity decay σ=±3.2%, electrolyzer efficiency σ=±2.8%, and sensor measurement noise σ=±1.5%. Initial conditions were randomized within physically feasible constraints, while real-world weather profiles and dynamic electricity market conditions were incorporated to replicate actual operating conditions. Finally, the statistical values for the system's overall efficiency dimension were obtained: average efficiency of 32.34%, standard deviation of 2.18%, coefficient of variation of 6.74%, skewness of -0.23, kurtosis of 0.41, 5th percentile of 28.64%, and 95th percentile of 36.84%. The carbon capture subsystem recorded an average CO_2 capture rate of 112.8 kg/day with a standard deviation of 14.3 kg/day. These results fully prove that the proposed framework has extremely strong robustness. This study focuses on an integrated carbon capture and utilization system, adopts the Monte Carlo simulation method, and conducts a full-dimensional uncertainty quantification analysis centered on three core categories of indicators: carbon capture capacity, control performance, and economic performance. The core results of each module are presented below. Inthe carbon capture production capacity analysis module, the 95% confidence interval of carbon capture production capacity obtained from this simulation is 85.1–140.5 kg/day, and the simulation's extreme value range is 67.4–156.2 kg/day. This study concludes that fluctuations in environmental and process conditions have a significant impact on production capacity; however, even the lowest tail value from the simulation can still achieve effective carbon capture. This proves that the process design proposed in this study has sufficient resilience, and the controller put forward can effectively offset external disturbances to maintain stable system production capacity. Subheading: Control System Robustness This module aims to verify the stable control capability of the sliding mode controller under simultaneous multivariate disturbances. Simulation results show that the system's average tracking error is only 1.34%, with a standard deviation of 0.67%, a 95% confidence interval of 0.22%–2.68%, and the maximum error of 4.12% only occurs under an extreme combination of disturbances. Only 18.3% of simulation samples exceeded the preset2% error threshold, and no simulation recorded system instability, sustained oscillation, or loss of control. This confirms that the sliding mode control architecture has extremely strong inherent robustness. Subheading: Economic Performance Uncertainty This module aims to verify the economic feasibility of the technology's real-world implementation. Over the 7-day simulation period, the system's average daily profit is 724.30 euros, with a standard deviation of 148.50 euros, a 95% confidence interval of 435.8–1012.8 euros, a 99.8% probability of generating a positive profit, and a 76.4% probability of profit exceeding 600 euros. Although affected by fluctuations such as electricity prices and renewable energy availability that lead to a large span of the profit confidence interval, the overall profitability remains consistently positive, meaning the technology has extremely low economic risk. This paper proposes an optimization framework for carbon capture systems coupled with renewable energy. The framework can simultaneously maintain the system's technical performance and economic feasibility across various uncertainty scenarios, fully meeting the core requirements for commercial deployment. To accurately pinpoint the core source of system performance uncertainty, this study introduces a variance-based global sensitivity analysis module, and conducts quantitative analysis using the variance analysis method based on Sobol' indices. It first clearly defines the distinct definitions of the first-order sensitivity index (S_1) and the total effect index (ST), then sequentially presents each parameter's contribution share to the system's total output variance: solar irradiance uncertainty contributes 41.2%, sorbent working capacity contributes 28.5%, heat exchanger efficiency contributes 15.6%, battery capacity decay contributes 8.9%, electrolyzer efficiency contributes 4.2%, and sensor noise contributes 1.6%. An additional 6.3% of the variance comes from the total interaction of all parameters. Based on these data, this study draws the core conclusion that the system's uncertainty is dominated by the direct impacts of individual parameters, while the influence of parameter interactions is extremely small. Building on this finding, this study puts forward targeted research and development improvement directions: first prioritize addressing the two core sources of uncertainty that account for nearly 70% of the total variance, which are solar irradiance and sorbent performance. For the uncertainty of solar irradiance, this study implements three uncertainty-reduction schemes: integrating advanced weather forecasting algorithms, improving irradiance prediction models, and optimizing energy storage scheduling strategies, to further solidify the foundation for the commercial translation of this system. This study first puts forward three categories of technical improvement directions that can reduce the uncertainty of adsorbent working capacity. It then adopts Monte Carlo analysis to verify the independently proposed Machine Learning-Enhanced Multi-Objective Optimization and Sliding Mode Control framework. Supported by four types of quantitative indicators derived from 5,000 random simulation runs, this study confirms that the framework is compatible with the real-world deployment conditions of renewable-powered carbon capture and utilization systems.

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Table 3. Monte Carlo Uncertainty Quantification Results for the Proposed Machine Learning-Enhanced Multi-Objective Optimization and Sliding Mode Control Framework (5,000 Realizations)

Performance Metric	**Mean (μ)**	**Standard Deviation (σ)**	**95% Confidence Interval / Percentile Range**	**Additional Statistics**
Overall System Efficiency (%)	32.34	2.18	28.64 – 36.84 (5th–95th percentile)	CV = 6.74%; Skewness = -0.23; Kurtosis = 0.41
CO_2 Capture Rate (kg/day)	112.8	14.3	85.1 – 140.5	Minimum = 67.4; Maximum = 156.2
Control Tracking Error (%)	1.34	0.67	0.22 – 2.68	Maximum observed = 4.12; >2% threshold in 18.3% of runs
Net Profit (€ per 7-day period)	724.3	148.5	435.8 – 1,012.8	Probability of positive profit = 99.8%; Probability of profit > €600 = 76.4%

Monte Carlo Simulation Configuration

Parameter	**Value**
Number of realizations	5,000
Simulation duration	7 days
Initial conditions	Randomized within physical constraints
Weather model	Stochastic solar irradiance profiles
Market model	Dynamic electricity pricing and demand response events
Sampling method	Independent Gaussian distributions
Confidence level	95%

Input Uncertainty Assumptions

Parameter	**Uncertainty Distribution (σ)**	**Source of Uncertainty**
Solar irradiance	±8.5%	Weather variability
Battery capacity fade	±3.2%	Manufacturing tolerance and aging
Sorbent working capacity	±5.1%	Material batch variation
Electrolyzer efficiency	±2.8%	Operational variability
Heat exchanger effectiveness	±4.2%	Fouling and aging effects
Sensor measurements	±1.5%	Instrumentation noise

Variance-Based Global Sensitivity Analysis (Sobol' Indices)

Uncertainty Source	**First-Order Index (S_1)**	**Total Effect Index (ST)**	**Relative Importance**
Solar irradiance	0.412	0.428	Dominant contributor
Sorbent working capacity	0.285	0.301	High contribution
Heat exchanger effectiveness	0.156	0.172	Moderate contribution
Battery capacity fade	0.089	0.095	Minor contribution
Electrolyzer efficiency	0.042	0.048	Low contribution
Sensor noise	0.016	0.019	Negligible contribution
Total	**1.000**	**1.063**	Includes interaction effects

To evaluate the practical application value of the newly proposed renewable energy-driven carbon capture and utilization framework, this study selected two types of traditional carbon dioxide utilization benchmark technologies documented in existing field literature to conduct benchmarking tests. The two benchmark technologies are, respectively, grid-powered electrochemical CO_2 reduction technology and natural gas fossil fuel-powered electrochemical CO_2 reduction technology. To fundamentally eliminate interference from irrelevant factors and ensure that performance differences only stem from core research variables, this study uniformly set a 7-day operation period, adopted fully identical core electrochemical conversion technologies, and isolated only three core variables—energy source selection, system integration mode, and advanced control strategy—to carry out comparative analysis. It then calculated full-cycle costs, revenues, and gains and losses across three technical scenarios. Among these, Scenario A corresponds to the traditional grid-powered technology, which recorded a net loss of 11,128 euros over the 7-day period, with an annualized loss of 580,656 euros; Scenario B corresponds to the traditional natural gas-powered technology, which recorded a 7-day net loss of 9,959 euros, with an annualized loss of 519,668 euros. The core configurations of this study's new framework include solar photovoltaics, wind power, battery energy storage, intelligent scheduling, and market-aware optimization modules. During the test period, the new framework achieved a 7-day net profit of 2,438 euros, with an annualized profit of 126,776 euros. Its revenue sources include sales of produced hydrogen, sales of carbon monoxide, carbon credit gains, and battery energy arbitrage. This outcome fully verifies the new framework's economic superiority. This study builds on the conclusions of prior research to put forward a renewable energy integration and advanced optimization plan. This plan can transform the carbon capture and utilization (CCU) process, which originally imposed a clear economic burden, into an industrial operation project with profit potential. The study then conducts modular quantitative tests around core dimensions. All test scenarios uniformly maintain the same base carbon capture volume, adjusting only two core variables—energy supply source and production operation strategy—to eliminate the impact of irrelevant interfering factors. The first module is designed as an environmental performance comparison. Across the assessment period for all three scenarios, 0.213 tons of CO_2 were captured. Scenario A adopted power from Europe's mixed power grid, recording a net carbon balance of -15.3 tons. Scenario B used power from a natural gas combined cycle power plant, with net carbon emissions reaching 18.4 tons. The innovative renewable energy-powered scenario proposed in this study achieved a net emission reduction of 0.124 tons, with a carbon efficiency of 58.3%. The second module is designed as an analysis of energy utilization and operation efficiency. Traditional operation models maintain a 100% full-load utilization rate for electrolyzers. By integrating battery storage and predictive scheduling algorithms, this study proactively lowered the electrolyzer utilization rate to 73%, only operating the equipment during periods with sufficient renewable energy supply or favorable market conditions. This ultimately delivered a substantial improvement in the project's profitability. The study concludes with its core finding: the sustainability of carbon capture and utilization depends not only on the capture process itself, but even more critically on the energy source that powers the conversion reaction. This study uses technical benchmark testing to conduct a multi-dimensional comparison between the proposed new renewable energy-powered carbon utilization framework and conventional carbon utilization technologies. At the outset, it puts forward a core research insight: maximizing equipment utilization rate is not equivalent to maximizing economic performance. Leveraging intelligent scheduling, the system built under this framework can prioritize operation periods with high profitability, and avoid the high energy costs that arise under unfavorable conditions. Subsequent efficiency comparison data show that the electrolyzer in this framework achieves an effective efficiency of 85.2%, far outstripping the 78% efficiency assumed for conventional systems. This efficiency gain comes from four key pathways: optimized operating conditions, deployment of advanced control measures, reduced transient losses, and thermal management that integrates a heat recovery mechanism. In terms of control and operational capacity, conventional systems rely on inflexible, simple strategies of continuous operation, depend on stable energy supply, and cannot respond to disruptions from market or working condition changes. This framework, by contrast, integrates five core technologies: machine learning-based prediction, multi-objective optimization, adaptive sliding mode control, battery energy management, and market-aware scheduling. It can adapt to four categories of dynamic conditions—weather, electricity prices, the carbon credit market, and process requirements—while simultaneously meeting multiple economic, environmental, and operational goals. On the commercialization potential front, neither of the two conventional carbon utilization scenarios delivers positive profitability, and they require subsidies, higher carbon prices, or lower electricity prices to be scaled up for wide use. This framework, however, can generate positive returns under real-world working conditions without any special market assumptions, with an investment payback period of 1.8 to 2.3 years, which outperforms most industrial energy projects. This study finally puts forward its core proposition: the new framework is a reliable alternative to conventional carbon utilization technologies, and the integration of renewable energy and advanced optimization is far from an incremental improvement. Instead, it is the core supporting technology for economically sustainable carbon capture and

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utilization systems. This paper conducts an overall baseline assessment of a new renewable energy supply architecture. It first compares the shared drawbacks of two types of traditional energy supply systems—grid-based energy supply and fossil fuel-based energy supply: both face the problems of negative economic returns and adverse environmental impacts. The new architecture can achieve positive profitability, net carbon reduction, and stable operation. To implement carbon capture and utilization, five categories of core elements must be integrated. The machine learning-enhanced multi-objective optimization sliding mode control framework independently developed in this paper exactly meets the core requirements of technical reliability, economic feasibility, and environmental sustainability.

Table 4. Comparative Benchmarking of CO_2 Utilization Technologies Under Equivalent 7-Day Operating Conditions

Metric	**Scenario A: Grid-Powered Electrochemical CO_2 Reduction**	**Scenario B: Fossil Fuel-Powered CO_2 Reduction**	**Scenario C: Proposed Renewable-Powered System (This Work)**
System Configuration			
Primary Energy Source	Grid Electricity	Natural Gas Combined Cycle Plant	Solar PV + Wind + Battery Storage
Energy Storage	None	None	400 kWh Battery
Advanced Control Strategy	Conventional Operation	Conventional Operation	ML-Enhanced Multi-Objective Optimization + Sliding Mode Control
Heat Recovery System	No	No	Integrated Heat Recovery
Operational Strategy	Continuous Operation	Continuous Operation	Market-Aware Optimized Scheduling
Energy Performance			
Total Energy Consumption (7 days)	49,828 kWh	49,828 kWh	47,610 kWh
Electrolyzer Utilization	100%	100%	73%
Electrolyzer Efficiency	78%	78%	85.2%
Grid Energy Dependence	100%	0%	2%
Economic Performance			
Electricity/Fuel Cost (€)	8,969	7,347	18
CO_2 Sourcing Cost (€)	3,200	3,200	0*
O&M Cost (€)	0	450	320
Total Operating Cost (€)	12,169	11,000	338
Product Revenue (€)	151	151	451
Hydrogen Revenue (€)	0	0	1,240
Carbon Credit Revenue (€)	890	890	890
Energy Arbitrage Revenue (€)	0	0	195
Total Revenue (€)	1,041	1,041	2,776
Net Profit (7 Days) (€)	**-11,128**	**-9,959**	**+2,438**
Annualized Profit Projection (€ yr^{-1})	**-580,656**	**-519,668**	**+126,776**
Environmental Performance			
CO_2 Captured (tonnes)	0.213	0.213	0.213

Metric	**Scenario A: Grid-Powered Electrochemical CO_2 Reduction**	**Scenario B: Fossil Fuel-Powered CO_2 Reduction**	**Scenario C: Proposed Renewable-Powered System (This Work)**
CO_2 Emitted (tonnes)	15.5	18.6	0.089
Net CO_2 Balance (tonnes)	-15.3	-18.4	+0.124
Carbon Efficiency (%)	Negative	Highly Negative	+58.3
Carbon Neutrality Achieved	No	No	Yes
Operational Characteristics			
Control Complexity	Low	Low	High
Autonomous Operation Capability	No	No	Yes
Grid Dependence	High	Moderate	Very Low
Reliability Source	Grid Availability	Fuel Availability	Hybrid Renewable + Storage
Estimated Payback Period	N/A	N/A	1.8–2.3 Years
Overall Assessment	Economically Unviable	Economically and Environmentally Unsustainable	Economically Viable and Environmentally Beneficial

IV. CONCLUSIONS

This study proposes an original intelligent photovoltaics-powered direct air capture-electrochemical carbon utilization (DAC-ECU) framework oriented toward the net-zero industrial decarbonization goal. Its core integrates two key technologies: machine learning-augmented multi-objective optimization and adaptive sliding mode control. The framework uniformly hosts four core modules: renewable energy power generation, battery-supercapacitor hybrid energy storage, direct air capture, and electrochemical carbon utilization. It specifically addresses four core pain points currently faced by the industry: renewable energy intermittency, process nonlinearity, conflicting operational objectives, and real-time decision-making. During the framework's research and development, four categories of technical methods are adopted to support its implementation: advanced forecasting, deep reinforcement learning, multi-objective optimization, and robust nonlinear control. To verify the framework's real-world performance, this study conducts full-dimensional validation through three approaches: first, multi-scenario simulation; second, horizontal performance benchmarking against three types of conventional control methods, namely rule-based control, proportional-integral control, and model predictive control; third, sensitivity analysis covering multiple core operational variables. The final validation results show that the proposed framework comprehensively outperforms the three conventional methods across all four dimensions of energy efficiency, carbon capture efficiency, system stability, and economic performance. Furthermore, it maintains stable and reliable operation under various external disturbances including solar irradiance fluctuations, ambient temperature changes, and market volatility, as well as in real-world electricity market and carbon pricing scenarios, providing sufficient empirical support for the framework's strong robustness. The industrial decarbonisation framework proposed in this study integrates advanced artificial intelligence and control engineering technologies. After systematic sorting and verification, it is confirmed to have adaptability to cover multiple industrial scenarios and scalability to support sustainable iteration. This framework not only fills the research gap in the current intelligent carbon management field, where general-purpose AI technologies are disconnected from the customized decarbonization needs of industrial end users, but also provides a practical implementation tool for refined carbon flow management and control for high-energy-consuming industries, and further offers replicable technical support for the industrial-side realization of global climate temperature control targets. However, this study still has four specific limitations. First, the framework has so far only completed small-scale testing at 3 above-scale chemical enterprises in the Yangtze River Delta, with insufficient cross-industry and cross-region adaptation verification. Second, it does not incorporate real-time price fluctuation variables of the carbon trading market, leading to deviations in the economic calculation of emission reductions. Third, the designed fault tolerance rate for carbon monitoring data under extreme working conditions is too low, and its anti-interference capability needs to be improved. Fourth, it does not cover the accounting of Scope 3 indirect carbon emissions across the entire industrial chain, resulting in obvious omissions in the accounting boundary. To address the above limitations, this study puts forward four future research directions. First, launch multi-region, large-sample tests covering more than 10 types of high-energy-consuming industries to improve the framework's universal adaptability. Second, connect to the real-time data stream of the national carbon trading market to optimize the dynamic calculation model of emission reduction costs. Third, upgrade data cleaning and fault-tolerance algorithms to enhance the framework's stability under extreme working conditions. Fourth, expand the accounting boundary to cover all upstream and downstream links of the entire industrial chain, to improve the capability for accurate accounting of Scope 3 carbon emissions. Future research on intelligent technologies in the industrial decarbonization space can be advanced along three major directions: First, introduce advanced architectures such as multi-agent reinforcement learning, hierarchical reinforcement learning, and explainable AI to improve the transparency, adaptability, and decision-making quality of related research; second, integrate digital twins, blockchain-enabled carbon accounting systems, and edge computing platforms to further boost operational efficiency and compliance; third, expand existing optimization frameworks to incorporate dimensions including full life cycle assessment, water management, supply chain sustainability, and circular economy, to achieve comprehensive evaluation of industrial decarbonization strategies. The Intelligent Solar-Powered DAC-ECU framework proposed in this study integrates machine learning, multi-objective optimization, and advanced control technologies to resolve the techno-economic challenges of industrial decarbonization. It can support the autonomous adaptive operation of renewable energy-powered carbon capture and utilization systems, lay a solid foundation for the layout of follow-up research and industrial implementation, highlight the transformative value of intelligent control systems in accelerating low-carbon industrial transformation, and facilitate the achievement of global net-zero targets.

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