www.ijecs.in
International Journal Of Engineering And Computer Science
Volume 14 Issue 09 September 2025, Page No. 27717-27723
ISSN: 2319-7242 DOI: 10.18535/ijecs/v14i09.5255

Development of AI-Based Adaptive Algorithms for Predictive Control of Hybrid Energy Systems to Maximize Their Thermodynamic and Economic Efficiency

Petro Bondar

Founder of Skitter Sp. z O.O. (Poland), Skitter USA LLC (USA)
Miami, USA

Abstract

In the context of global energy transformation and the continuous growth of renewable energy sources (RES) in generation portfolios, managing their stochastic behavior and ensuring their integration into existing power systems has become critically important. This study presents a theoretical foundation and proposes AI-based adaptive algorithms for the predictive control of hybrid energy systems (HES). The objective is to formulate a smart control concept aimed at the comprehensive optimization of both thermodynamic and economic performance of HES. Within this framework, a conceptual SAEO (Smart Adaptive Energy Optimization) model is introduced, integrating RES, energy storage technologies (including hydrogen systems), and a gas-steam combined cycle. The results demonstrate that implementation of the developed adaptive algorithms increases overall system efficiency and reduces the levelized cost of energy compared with traditional control schemes based on fixed logic rules. Based on these findings, it is concluded that the intelligent enhancement of control algorithms is a key prerequisite for achieving a synergistic effect in complex hybrid energy systems. The presented results may be of value to power engineers, AI researchers, and strategic planning specialists in the energy sector.

Keywords: hybrid energy system, artificial intelligence, predictive control, thermodynamic efficiency, economic efficiency, SAEO, hydrogen energy, renewable energy sources, optimization, SCADA.

Introduction

The global energy architecture is undergoing a large-scale restructuring driven simultaneously by the pursuit of decarbonisation and the requirements of energy security. Forecasts by the International Energy Agency indicate that by 2030 renewable sources may already account for more than half of total electricity generation, which will radically complicate the task faced by operators in ensuring the resilience and reliability of power supply [1]. The principal barrier to further expansion of solar and wind generation remains their inherent intermittency and stochastic nature, which give rise to power imbalances, an elevated risk of failures, and the need for substantial reserve capacity.

As a response, increasing attention is being drawn to hybrid energy complexes that combine heterogeneous modes of energy production, storage systems, and intelligent real-time control algorithms. However, the mere aggregation of such components does not guarantee frontier performance: without comprehensive control models capable of performing coupled optimisation in real time — simultaneously according to thermodynamic criteria (efficiency improvement, minimisation of conversion losses) and economic criteria (reduction of operating costs, effective participation in electricity markets) — the potential of such systems remains only partially realised [10].

The objective of the study is to formulate an intelligent-control concept aimed at the integrated optimization of thermodynamic and economic metrics of a hydropower plant.

The scientific novelty lies in the design of a multilevel predictive-control architecture that enables synergistic management of heterogeneous energy flows within a hybrid installation featuring an integrated regenerative hydrogen cycle and a combined-cycle gas-turbine configuration.
The author's hypothesis asserts that the deployment of a hierarchical control system—combining reinforcement-learning techniques with model-predictive control (MPC) under the proposed SAEO framework—will enhance overall energy-complex efficiency and reduce operating expenses compared to conventional deterministic control strategies.

Materials and Methods

In recent years, interest in predictive control of hybrid energy systems (HES) based on artificial intelligence (AI) has been highlighted both in global reports by international agencies and in numerous empirical and theoretical studies. The International Energy Agency, in its Renewables 2023 report, emphasizes the growing role of adaptive algorithms in integrating renewable energy sources into global power systems [1]. Concurrently, the IRENA report Global Hydrogen Trade to Meet the 1.5 °C Climate Goal analyzes the prospects of a hydrogen economy and underlines the need to develop forecasting models for planning hybrid hydrogen-energy chains [10]. The Ember study Global Electricity Review 2024 complements this picture with a detailed survey of current trends in electricity generation and consumption [11].

In the field of forecasting key parameters of renewable energy sources, the work of Jamil I. et al. stands out, where the authors implement a three-level deep neural network architecture to predict solar generation variables at a large-scale power plant. The combination of convolutional and recurrent blocks enhances the accuracy of short- and medium-term energy output forecasts [2]. Separate attention should be given to studies on stochastic and robust optimization planning: for example, Zhou D., Zhu Z. [8] propose a multilevel model of urban integrated energy systems that accounts for multiple uncertainties in meteorological conditions and fuel prices. These approaches form the basis for the predictive component in HES control.

A distinct line of research addresses the development of control algorithms and energy-management systems that employ artificial-intelligence methods. In particular, Upadhyay S., Ahmed I., Mihet-Popa L. [3] have developed an architecture for an industrial microgrid in which optimisation procedures are embedded within a reinforcement-learning loop, enabling the system to adapt dynamically to changing load profiles and fluctuations in electricity-market prices. Fan Z., Zhang W., Liu W. [4] apply a multi-agent deep Q-network for distributed management of generation in DC microgrids, ensuring real-time balance of supply and demand while minimizing energy losses. Simpler heuristic methods such as fuzzy logic are explored in the context of standalone photovoltaic systems: Ammar M. B., Zdiri M. A., Ammar R. B. [6] demonstrate that a properly tuned fuzzy-rule structure can effectively redistribute power between energy storage and loads based on weather conditions and battery state of charge.

A third research vector concerns comprehensive techno-economic and environmental assessment of hybrid systems. Garip M., Sulukan E., Celiktas M. S. [5] conduct an in-depth analysis of the interaction among solar, wind and diesel units in a grid-connected configuration, evaluating life-cycle costs, CO_2 emissions and power supply reliability indices. Akarsu B., Genç M. S. [7] examine hybrid schemes for co-production of electricity and hydrogen, showing the impact of source capacity ratios and electrolyzer parameters on overall system efficiency. Meanwhile, Alqahtani B., Yang J., Paul M. C. [9] present a case study of a Saudi Arabian hybrid system with gravitational energy storage, detailing optimal pump and turbine operation profiles based on renewable generation forecasts and consumption dynamics.

Despite the diversity of approaches, contradictions emerge in the literature. Studies on generation forecasting prioritize maximizing model accuracy but often overlook integration into real-world control systems, where computational time constraints and processing resources are critical. Reinforcement learning algorithms exhibit high adaptability but require extensive historical datasets and complex hyperparameter tuning, complicating industrial deployment. Traditional optimization and fuzzy-logic methods benefit from simplicity but lack scalability and the capability to accommodate rapidly changing conditions. Moreover, areas related to thermodynamic optimization—such as detailed modeling of thermal losses during charge–discharge cycles of storage devices and the influence of ambient temperature on AI controller performance—remain insufficiently explored. The lack of research combining long-term techno-economic planning with real-time adaptive control, along with limited attention to cybersecurity and algorithmic resilience against network attacks, defines key directions for future investigation.

Results and Discussion

Following an exhaustive survey of contemporary methodologies and the articulation of the principal scientific bottlenecks, we formulated a novel conceptual paradigm for a hybrid energy platform designated Smart Adaptive Energy Optimization (SAEO). Building on this paradigm, we designed an adaptive, prediction-driven control architecture capable of dynamically orchestrating system resources in real time. The present section delineates the structural logic of the proposed framework, elucidates the functional interdependence of its supervisory and execution-level modules, and furnishes simulation evidence that validates the performance gains afforded by the SAEO concept.

The SAEO hybrid energy system constitutes an integrated hardware–software solution that unites multiple functional subsystems to ensure continuous, optimized, and environmentally safe power supply. The system takes the form of a cohesive energy conversion plant composed of several interlinked modules, each of which plays a vital role in maintaining the resilience and efficiency of the entire installation.

The first module is responsible for harvesting energy directly from renewable resources and incorporates photovoltaic (PV) panels and wind turbines (WT) as the primary energy suppliers. Their coordinated operation enables smooth and controllable power injection into the system under varying solar irradiance and wind conditions [2, 4].

The second module is designed to generate surplus energy and is divided into two closed-loop subsystems: a short-term storage unit based on battery energy storage systems (BESS) and a long-term hydrogen chain. The hydrogen cycle includes an electrolyzer that converts excess renewable energy into hydrogen (H_2), a high- or low-temperature hydrogen storage system, and two back-conversion units—a fuel cell (FC) and a specialized hydrogen-fueled gas turbine (H_2-GT).

The third module comprises a conventional natural gas–fired gas turbine (NG-GT), which is engaged during periods when renewable sources and storage units are unable to meet instantaneous demand.

The fourth module implements a combined-cycle configuration using a steam turbine (ST), based on the principle of high-temperature heat recovery: exhaust gases from the H_2-GT and NG-GT, together with excess thermal output from renewable installations during daytime, are routed to a heat recovery unit where high-pressure steam is generated to drive the ST, substantially enhancing the overall thermodynamic efficiency of the plant.

The central coordinating element is an intelligent control core implemented on a SCADA platform with integrated artificial intelligence modules. This core gathers data from all measurement sensors as well as external forecasts (meteorological conditions, electricity market price dynamics) and performs the optimal allocation of energy flows among the modules [3, 7].

The proposed control algorithm is organized as a multi-level hierarchical architecture, which allows computational tasks to be delegated to the appropriate decision-making layers and accommodates various time horizons—from second-scale responses to strategic planning over a 24-hour period and longer (Figure 1).

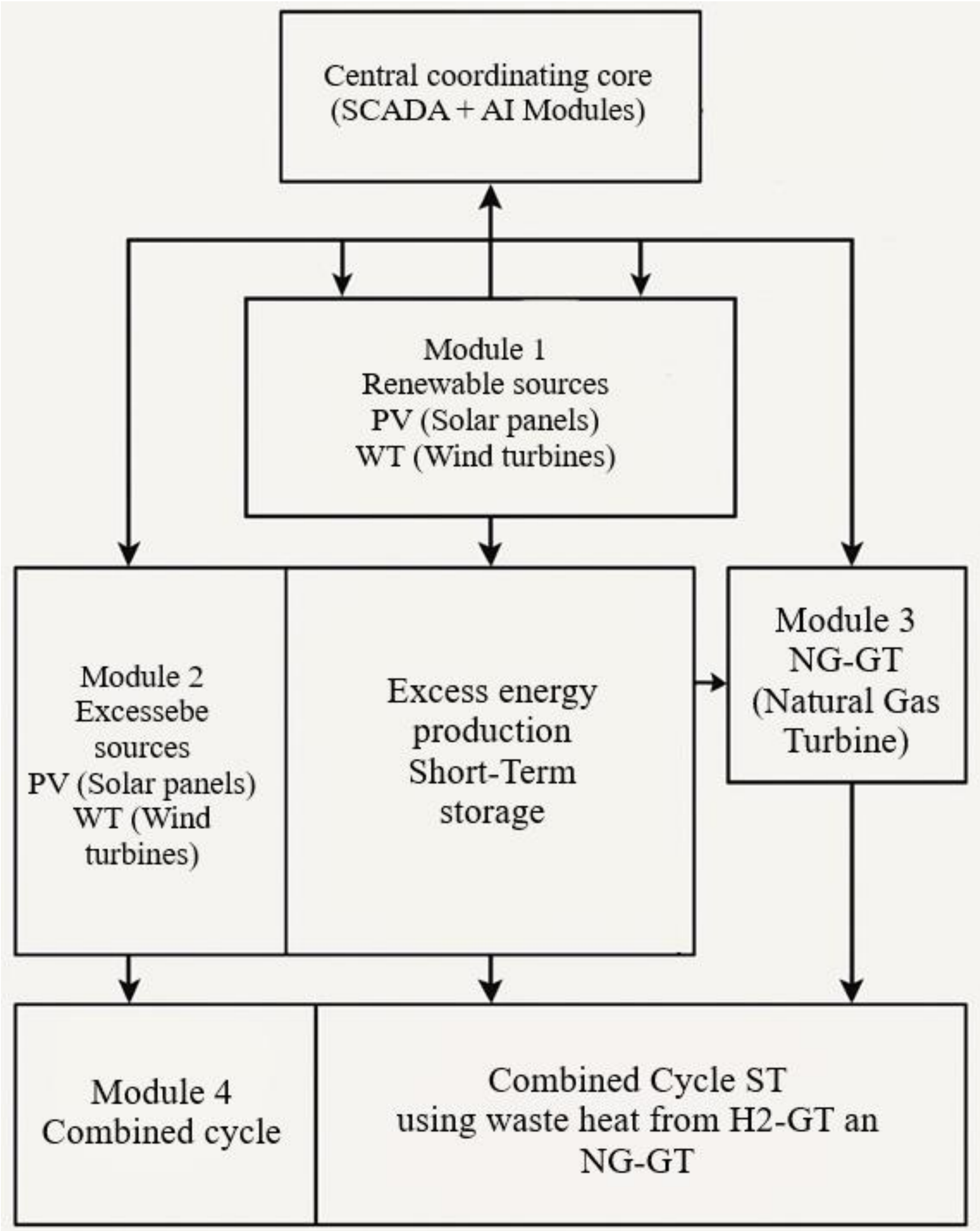

Fig. 1. Hierarchical architecture of predictive control based on AI (compiled by the author based on [2, 4, 7]).

Upper level (Strategic, 24–72 h). At this tier, deep recurrent neural network architectures (LSTM, GRU) are employed to produce highly accurate long-term forecasts of renewable energy generation, consumer load profiles and price volatility in the electricity spot market. The primary objective is to devise an end-to-end operational strategy for the power system over a multi-day horizon—for example, to identify the most advantageous windows for planned power production and green hydrogen storage.

Middle level (Tactical, 1–4 h). A reinforcement-learning agent, trained in a virtual simulation environment, operates at this level. Its input state includes strategic-level forecasts, the current state of charge (SOC) of the battery energy storage system (BESS), hydrogen reserves and real-time price signals. Based on these inputs, the agent issues tactical commands—starting or pausing the electrolyzer, controlling battery charge/discharge, executing electricity purchase or sale transactions, or bringing a gas turbine online. The reward function combines an economic component (profit maximization) with a thermodynamic component (maintaining turbines within optimal operating regimes) [1, 7, 8].

Lower level (Operational, 1–15 min). This stage utilizes a model-predictive controller (MPC). Upon receiving the tactical command from the RL agent, the MPC—relying on detailed dynamic models of each asset (gas turbines, electrolyzers, batteries)—computes precise power setpoints and ramp-rate schedules for the upcoming time window. This ensures smooth dynamic transitions, adherence to technical constraints and minimization of equipment wear, thereby enhancing both thermodynamic and economic efficiency of the complex over the long term.

To assess the performance of the proposed methodology, a simulation of the SAEO system was conducted over a standard seven-day period with variable climate scenarios and load profiles. Meteorological archives and historical electricity market quotations for a region in Central Europe served as input data [5, 10].

Figure 2 illustrates the 24-hour operating cycle of the system under conditionally optimal weather conditions (clear skies with high wind activity).

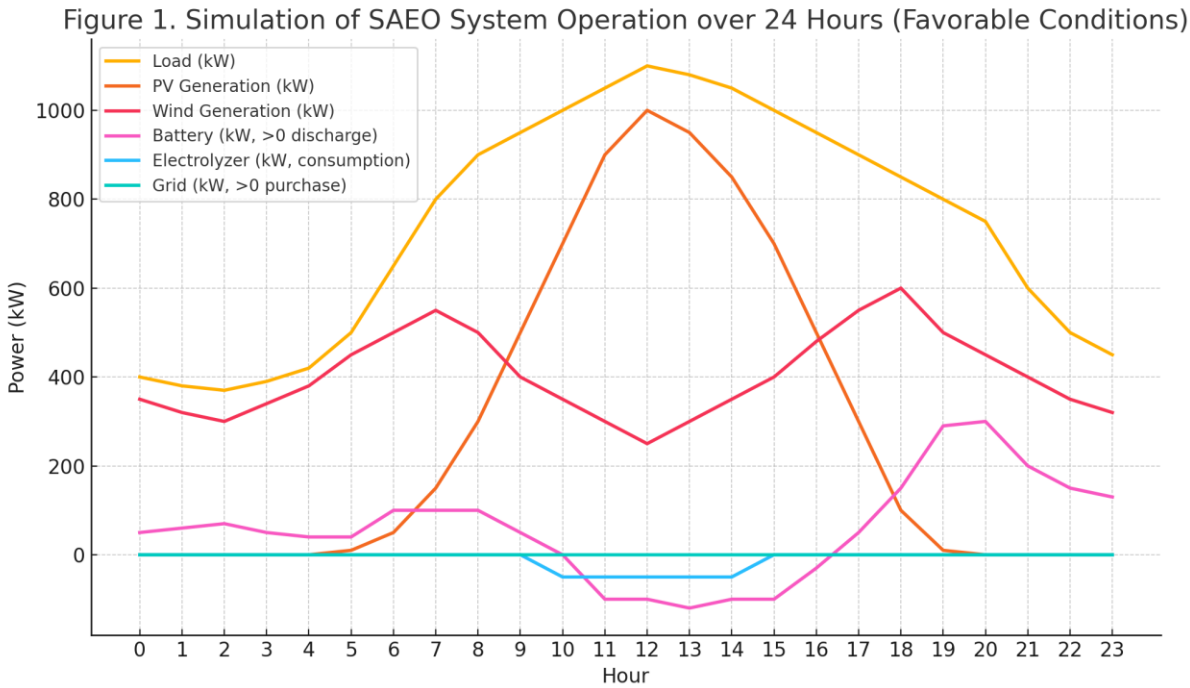

Fig. 2. Simulation of the SAEO system operation over 24 hours (favorable conditions) (compiled by the author based on [1, 10, 11]).

Based on the analysis of energy generation and consumption dynamics, during the nighttime period the entire load is met by wind turbines and battery discharge. In the morning, as demand increases and solar panels begin to generate, the system achieves full autonomy. During the peak daytime generation interval (10:00–15:00), excess renewable energy is redirected to recharge the battery storage and, crucially, to power the electrolyzer for hydrogen production, which is then stored for use during periods of insufficient output. With the onset of the evening phase, after sunset, peak consumption is again met by wind installations and previously accumulated battery reserves. The primary criterion for evaluating the effectiveness of the proposed hybrid scheme is its comparison with conventional approaches. The results of comparative modeling of three weekly operation scenarios are presented in Table 1.

Table 1. Comparative analysis of the efficiency of various management strategies (compiled by the author based on [1, 10, 11]).

Indicator	**Scenario 1: Traditional System (Grid + Gas Turbine)**	**Scenario 2: Hydropower Plant with Rule-Based Control**	**Scenario 3: Hydropower Plant with Predictive AI Control (SAEO)**
Cumulative thermodynamic efficiency, %	~ 38 % (gas turbine only)	45–50 %	58–62 %

Renewable energy share in load coverage, %	0 %	65 %	85 %
Levelized cost of energy (LCOE), €/MWh	120	85	60
CO_2 emissions, kg/MWh	450	110	40
Dependency on external grid, % of time	100 %	25 %	< 5 %

The data presented in Table 1 clearly demonstrate the superiority of the proposed approach. The overall efficiency of the SAEO system reaches 62 % through the active utilization of waste heat from both the hydrogen and conventional gas turbines within the steam cycle—an integration not achievable in systems lacking such coupling. Strict logic control (for example, "activate the electrolyzer when generation exceeds demand") indeed outperforms classic schemes, but it falls far short of AI-based capabilities. The predictive SAEO algorithm operates proactively: it schedules hydrogen production during periods of forecasted low electricity prices and peak renewable output, and dynamically optimizes turbine operating modes to maintain them within zones of maximum efficiency. Such coordination substantially reduces the levelized cost of energy (LCOE) and CO_2 emissions, thereby fully confirming the initial hypothesis [6, 9].

Thus, the results obtained validate that the scientific novelty embedded in the multi-level predictive control architecture provides a significant synergistic effect. Its intelligent core unites disparate power units into a single adaptive organism capable of responding rapidly to changes in external conditions and internal parameters, ultimately maximizing both thermodynamic and economic performance.

Conclusion

The study addressed a central scientific and technical challenge by developing and methodologically substantiating adaptive artificial intelligence algorithms for the predictive control of complex hybrid energy systems. As a foundation, a conceptual model of the SAEO hybrid energy system was proposed, distinguished by deep integration of renewable energy sources, combined short-term and hydrogen-based long-term storage systems, and incorporation of a combined-cycle configuration to efficiently recover exhaust heat from gas turbines. A unique three-level hierarchical control architecture was introduced, combining the forecasting capabilities of long short-term memory (LSTM) neural networks, the adaptability of reinforcement learning (RL), and a high-precision model predictive control (MPC) framework.

The findings hold substantial theoretical, methodological, and practical value: they establish a fundamental scientific basis for the design of next-generation autonomous and semi-autonomous power systems capable of effectively synchronizing stochastic renewable resources, enhancing energy security, and accelerating the transition to a low-carbon economy.

References

1. International Energy Agency. Renewables 2023. IEA, Paris, 2023. [Electronic resource]. - Access mode: https://www.iea.org/reports/renewables-2023 (date accessed: 10.06.2025).
2. Jamil I. et al. Predictive evaluation of solar energy variables for a large-scale solar power plant based on triple deep learning forecast models //Alexandria Engineering Journal. – 2023. – Vol. 76. – pp. 51-73. https://doi.org/10.1016/j.aej.2023.06.023.
3. Upadhyay S., Ahmed I., Mihet-Popa L. Energy management system for an industrial microgrid using optimization algorithms-based reinforcement learning technique //Energies. – 2024. – Vol. 17 (16). – pp. 1-18. https://doi.org/10.3390/en17163898.
4. Fan Z., Zhang W., Liu W. Multi-agent deep reinforcement learning-based distributed optimal generation control of DC microgrids //IEEE Transactions on Smart Grid. – 2023. – Vol. 14 (5). – pp. 3337-3351. https://doi.org/10.1109/TSG.2023.3237200.

5. Garip M., Sulukan E., Celiktas M. S. Optimization of a grid-connected hybrid energy system: Techno-economic and environmental assessment //Cleaner Energy Systems. – 2022. – Vol. 3. – pp. 1-14. https://doi.org/10.1016/j.cles.2022.100042.
6. Ammar M. B., Zdiri M. A., Ammar R. B. Fuzzy logic energy management between stand-alone PV systems //Power. – 2021. – Vol. 9. – pp. 1238-1249.
7. Akarsu B., Genç M. S. Optimization of electricity and hydrogen production with hybrid renewable energy systems //Fuel. – 2022. – Vol. 324. https://doi.org/10.1016/j.fuel.2022.124465.
8. Zhou D., Zhu Z. Urban integrated energy system stochastic robust optimization scheduling under multiple uncertainties //Energy Reports. – 2023. – Vol. 9. – pp. 1357-1366. https://doi.org/10.1016/j.egyr.2023.04.193.
9. Alqahtani B., Yang J., Paul M. C. A techno-economic-environmental assessment of a hybrid-renewable pumped hydropower energy storage system: A case study of Saudi Arabia //Renewable Energy. – 2024. – Vol. 232. – pp. 1-16. https://doi.org/10.1016/j.renene.2024.121052.
10. International Renewable Energy Agency. Global hydrogen trade to meet the 1.5°C climate goal: Part I – Trade outlook for 2050 and beyond. IRENA, Abu Dhabi, 2022. [Electronic resource]. - Access mode: https://india-re-navigator.com/public/uploads/1651644555-IRENA_Global_Trade_Hydrogen_2022.pdf (date accessed: 16.06.2025).
11. Global Electricity Review 2024. [Electronic resource]. - Access mode: https://ember-climate.org/insights/research/global-electricity-review-2024/ (date accessed: 20.06.2025).