

Machine Learning Applied to Pumped-Storage Hydropower Operation for Solar Curtailment Mitigation: A Systematic Review of the Brazilian Power System

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Abstract

This study aims to evaluate how machine learning algorithms can be used to reduce solar generation curtailment by operating pumped-storage hydropower plants. This analysis was conducted through a systematic literature review, characterized by an organized and rigorous investigation of previously published studies. Three main types of sources were considered: high-impact scientific articles, recent systematic reviews, and official Brazilian energy planning documents. An examination of internationally published research showed that control techniques applied to renewable energy systems have become increasingly sophisticated. The research frontier has advanced toward deep reinforcement learning, in which an artificial intelligence agent learns through trial and error to make operational decisions without relying on rigid mathematical models. The evaluated algorithms demonstrated the ability to reduce renewable energy waste, minimize equipment degradation, and maximize revenue. However, upon assessing the existing body of research, a significant gap in the literature was identified: recent studies have not explored the use of artificial intelligence-operated pumped-storage hydropower plants within the context of the Brazilian electric power system. This combination emerges as a promising and, to date, unprecedented solution for enhancing the flexibility of the electric grid and more effectively harnessing Brazil's solar energy potential.

Keywords

Machine Learning, pumped-storage hydropower plants, solar generation curtailment

1. Introduction

The transition toward a lower-carbon electricity matrix has driven the expansion of renewable sources, with photovoltaic solar energy emerging as an increasingly prominent option. In Brazil, this expansion is particularly promising, given the country's vast available land area and favorable solar resources. According to [1], average solar radiation levels are high and relatively stable throughout the year, exhibiting only minor variations across seasons and years. These average global horizontal irradiance levels exceed those observed in several European countries where photovoltaic technology is already widely deployed, such as Germany, Spain, Italy, Portugal, and France, indicating that Brazil holds even greater potential than these nations at the forefront of solar energy adoption. In this context, the Central-West region stands out for presenting average daily horizontal-plane radiation values of approximately 5.10 kWh/m², indicating excellent conditions for photovoltaic deployment.

The growing share of photovoltaic and wind generation has introduced new operational challenges for the Brazilian National Interconnected System (BNIS), given that the output of these variable renewable sources is independent of operator decisions. The Energy Research Company (ERC) [2] notes that, as photovoltaic capacity increases, net load decreases during daytime hours, since solar generation meets part of the demand, but rises sharply in the late afternoon and early evening, as the sun sets

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and photovoltaic output declines abruptly. Under these conditions, the generation fleet must exhibit high flexibility to increase or decrease output within short time intervals. Consequently, hydroelectric plants, thermal power plants, and other sources must follow steeper net-load ramps precisely at the onset of the evening period, in order to compensate for the sudden drop in solar generation [3, 4]. In systems with high penetration of variable renewables, insufficient grid infrastructure and plant flexibility tend to increase curtailment, that is, cuts to renewable generation even when solar or wind resources remain available. As discussed by authors such as [5], this process reduces the economic viability of renewable projects due to flexibility and grid limitations in modern systems characterized by high shares of variable sources.

As the share of variable renewable sources such as solar and wind continues to grow within the global electricity matrix, large-scale energy storage systems have become central to maintaining the balance between generation and consumption. Moreover, they play a fundamental role in preserving power quality and supply reliability [4]. Under conditions of increased generation variability, storage functions as a “buffer” that helps maintain system stability. Historically, Brazil has been able to postpone adopting dedicated storage technologies, given its reliance on hydroelectric plants with large reservoirs, which have long fulfilled this battery-like role. Nevertheless, the ERC recognizes Pumped-Storage Hydropower Plants (PSHPs) as a mature, efficient, and important solution, capable of providing firm capacity, operational flexibility, and support for greater integration of renewable sources. On a global scale, PSHPs account for more than 95% of all large-scale electrical energy storage capacity, demonstrating that large-scale storage within the electricity matrix is, in general, synonymous with the role played by these plants [3, 4, 6]. At the same time, the growing operational complexity of these storage assets, together with hybrid arrangements that combine renewables and Energy Storage Systems (ESS), has driven the search for more advanced control strategies, in which artificial intelligence increasingly plays a significant role.

Nevertheless, operating arrangements that combine solar generation, batteries, and loads are not a trivial task, particularly because such systems are subject to climatic uncertainties, such as irradiance variability, as well as energy price volatility and demand fluctuations. These factors render the control problem considerably more complex than simply following a predetermined routine. In this scenario, researchers and operators have pursued more sophisticated strategies that combine optimization techniques and machine learning to achieve more efficient energy management. Within this context, Machine Learning (ML) algorithms emerge as promising tools, as they can learn, through trial and error in simulated or real environments, dispatch policies that maximize revenue and reduce curtailment in hybrid systems and solar-storage arrangements. Several studies show that ML can learn to operate such systems more profitably and with reduced waste of renewable energy [7, 8, 9].

Among existing systematic reviews, one consolidated review addresses photovoltaic generation forecasting using ML [10], examining how artificial intelligence models are employed to improve solar power output prediction. Another review addresses the use of ML techniques in energy storage systems, focusing primarily on lithium-ion batteries and other ESS, covering aspects such as control, diagnostics, and circularity [11]. A third review synthesizes the main drivers and barriers associated with the development of PSHPs, including socio-environmental factors [6]. Taken together, these three reviews indicate that robust knowledge already exists regarding ML-based forecasting, ML applied to batteries, and the deployment context of PSHPs. However, a specific type of review remains absent: one that consolidates the state of the art regarding the use of ML techniques, particularly advanced methods such as Deep Reinforcement Learning, applied directly to PSHP operation with the aim of mitigating solar curtailment, while accounting for the particularities of the large-scale hydrothermal system that characterizes the Brazilian case.

Therefore, in light of the discussion presented above, this study follows the PRISMA protocol to conduct a rigorous and transparent systematic review, aiming to critically analyze how artificial intelligence algorithms have been employed to optimize the dispatch of large-scale storage systems. This review does not merely catalog existing studies; it seeks to map which neural architectures have proven most effective in high-impact publications while assessing whether such solutions can be adapted and applied to the Brazilian electric power sector. Finally, by bridging state-of-the-art ML with the real

flexibility challenges of the BNIS, this study aims to provide a theoretical framework to support future research on system optimization and to contribute to the country's energy transition.

The remainder of this paper is organized as follows. Section 2 describes the systematic-review methodology, including the PRISMA-based protocol, research questions, search strategy, eligibility criteria, and screening process. Section 3 presents and discusses the results; it also compares the reported quantitative results and examines the research gap concerning PSHP operation in the Brazilian context. Finally, Section 4 summarizes the main findings, highlights the identified limitations and knowledge gaps, and outlines directions for future research.

2. Materials and methods

This study followed the PRISMA 2020 protocol [12], which ensures transparency, methodological quality, and reproducibility in systematic reviews. The methodology steps, detailed in the following sections, are shown in Figure 1.

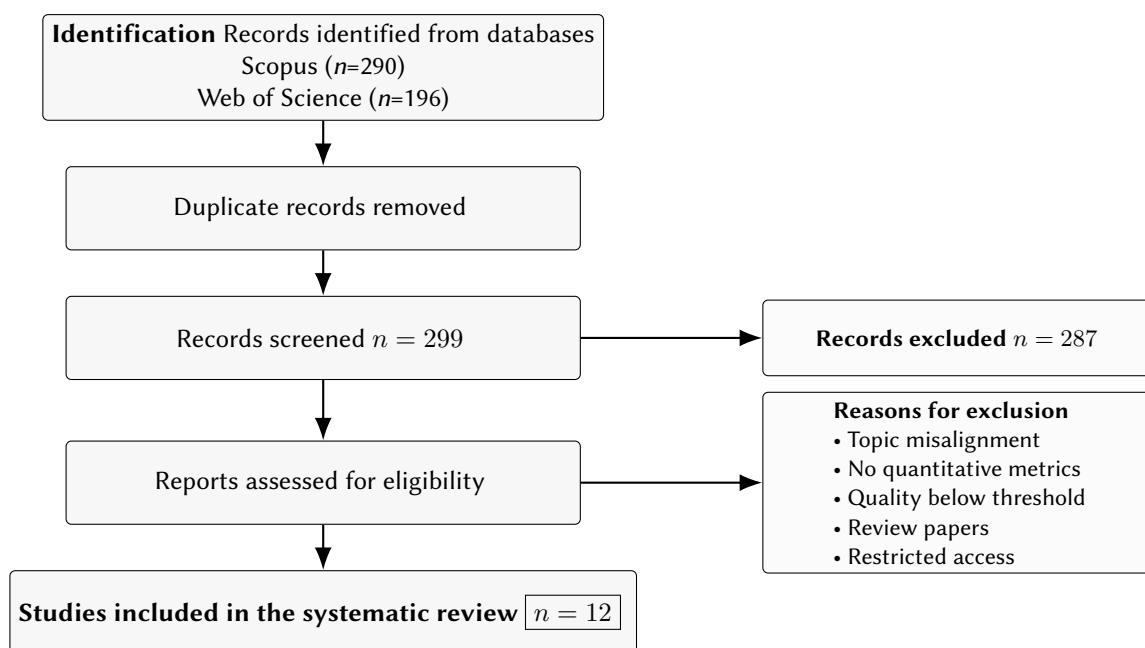


Figure 1: PRISMA-based flow diagram of the study selection process.

2.1. Research questions

This systematic review was guided by four research questions (RQs), structured according to the PRISMA 2020 framework:

- **RQ1:** Which machine learning and AI approaches have been applied to energy storage operations or energy management to mitigate solar photovoltaic curtailment?
- **RQ2:** Which system configurations, storage technologies, operational objectives, and performance metrics are addressed in the selected studies?
- **RQ3:** What quantitative benefits and limitations are reported, particularly regarding curtailment reduction, renewable energy utilization, operational costs, revenue, grid support, and equipment degradation?
- **RQ4:** To what extent has machine learning, especially deep reinforcement learning, been applied to real-time operation of pumped-storage hydropower for solar-curtailment mitigation in the Brazilian National Interconnected System?

These questions aim to identify the state of the art in AI-based management of storage-supported renewable systems and assess how the evidence can support future pumped-storage hydropower solutions in Brazil.

2.2. Search strategy

The search was conducted in Scopus and Web of Science (2015–2026). The strategy combined terms addressing RQ1 and RQ2 – artificial intelligence, solar curtailment, energy storage, and photovoltaic generation – while RQ3 and RQ4 guided the extraction and interpretive synthesis of evidence.

The search string combined four core concepts: artificial intelligence (e.g., machine learning, deep learning), energy curtailment (e.g., curtailment, solar curtailment), energy storage (e.g., energy storage, pumped hydro storage), and solar energy (e.g., solar energy, photovoltaic). Results were restricted to journal and conference papers in engineering, energy, computer science, mathematics, and environmental sciences.

The search string used for the is presented below:

```
((("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning") AND ("Curtailment"
OR "Solar Curtailment") AND ("Energy Storage" OR "Pumped Hydro Storage" OR "PHS" OR
"Hydropower" OR "Storage System*")) OR (("Machine Learning" OR "Artificial
Intelligence") AND ("Solar Energy" OR "Photovoltaic*") AND ("Energy Management" OR "
Grid Integration") AND ("Storage"))
```

2.3. Eligibility criteria

The inclusion and exclusion criteria below ensured that selected articles met the relevance and quality standards required for the final analysis. Eligibility was defined to retain primary studies relevant to the four RQs. A study was eligible if it simultaneously met:

- **Publication type:** Primary study published in a peer-reviewed journal or conference proceedings (2015–2026).
- **Publication quality:** High-impact venue, defined as CiteScore ≥ 4.7 or Journal Impact Factor (JIF) ≥ 1.4 .
- **Thematic alignment:** Integrated coverage of the four research pillars – AI applied to solar curtailment management using energy storage systems.

A study was excluded if it presented any of the following:

- **Article type:** Review article, meta-analysis, or editorial.
- **Lack of alignment:** Did not clearly address the intersection of the four core themes.
- **Absence of quantifiable results:** No performance metrics or results allowing objective analysis.
- **Insufficient methodological quality:** Results not supported by the evidence provided.
- **Restricted access:** Not available through open access or institutional subscriptions.

2.4. Screening process

The selection process applied the following criteria:

- **Bibliographic search:** Scopus and Web of Science yielded 299 articles after duplicate removal, imported into a control spreadsheet for systematic screening.
- **Title and abstract screening:** Titles, abstracts, and keywords of the 299 articles were screened against the inclusion and exclusion criteria.

This process excluded 287 articles:

- **Lack of thematic alignment (165):** Did not simultaneously address the four core concepts.
- **Absence of metrics:** No quantitative results presented.
- **Below quality threshold (28):** CiteScore or JIF below the predetermined minimum.
- **Review articles (18):** Not original research works.
- **Restricted access (1):** Paywalled.

Ultimately, 12 articles were selected for detailed analysis.

3. Results and discussion

The 12 selected articles were grouped into three research lines: planning, predictive control, and real-time DRL. This classification addresses RQ1 (AI-based approaches) and RQ2 (operational contexts); the quantitative evidence per group addresses RQ3, while the absence of PSHP-focused applications in the Brazilian context addresses RQ4.

The first group covers optimization of planning and sizing of hybrid systems — determining, prior to operation, the appropriate sizes of solar, wind, battery, and hydrogen subsystems. The second group addresses predictive control and forecast-based management, using generation and demand forecasts to guide operation and reduce curtailment. The third group covers real-time adaptive control via DRL, where agents learn control policies directly from environment interaction, without relying as rigidly on fixed forecasts.

Figure 2 shows the evolution of ML-based approaches across these groups, discussed further in the following subsections.

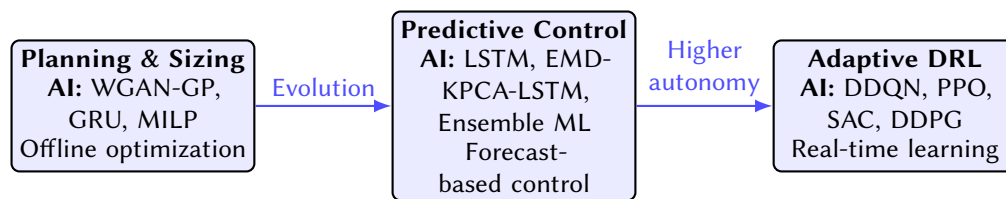


Figure 2: Evolution of ML-based approaches for renewable energy management.

3.1. Planning and sizing optimization

The first group addresses the planning problem — determining optimal asset capacity prior to operation. This is critical, since inadequate sizing compromises both technical performance and economic viability. The three studies in this group [13, 5, 7] adopt distinct approaches but converge on the same conclusion: integrating machine learning into planning yields superior results compared to traditional deterministic methods.

Ma et al. [13] proposed a two-stage approach for optimal sizing of hybrid wind-PV systems with storage. First, a Wasserstein GAN with Gradient Penalty (WGAN-GP) generated nine typical wind and solar production scenarios to more robustly represent renewable resource variability and uncertainty. Second, these scenarios fed a multi-objective optimization model solved via the Sparrow Search Algorithm (SSA), reported to offer faster convergence, higher search precision, and greater robustness than alternatives such as PSO and GWO. Validated in a case study in northwestern China, the framework reduced curtailment by 3.6%–14.7% compared with scenarios without storage.

Shams et al. [5] examined curtailment recovery from variable renewable sources through optimal utilization planning of Alkaline Water Electrolyzers (AWEs) for hydrogen production and Lithium-Ion Batteries (BESSs), using a two-stage stochastic model to determine equipment sizing and operation. The main innovation was a Gated Recurrent Unit (GRU) neural network for curtailment forecasting — an assessment the authors state had not been conducted previously — which reduced forecast errors.

Economically, AWE recovered 97% of curtailment at an annual cost of USD 233.5 million, 63.5% lower than BESS (which recovered only 79%). The authors attribute this advantage to electrolyzers' longer service life (80,000–90,000 hours) versus batteries (3,500 cycles), making AWE more viable for long-term operations.

Rehman et al. [7] analyzed a monitored building in Central Europe, proposing a hybrid framework combining machine learning and mathematical optimization for an integrated PV-battery storage-EV charging system (PV-BESS-EV). Machine learning was first used as a data treatment step to identify short-term events and reconstruct series consistent with the building's actual load behavior. An optimization model based on Mixed-Integer Linear Programming (MILP) was then formulated to evaluate sizing and operational alternatives across system configurations. Methodologically, the study underscores the importance of integrating data-driven preprocessing with deterministic optimization to assess distributed energy systems in buildings.

3.2. Predictive control and forecast-based management

The second set of articles does not focus solely on planning but advances toward the operation of the system itself. These studies test control strategies that use generation and demand forecasts; that is, they seek to anticipate the system's future state to make more efficient dispatch decisions [14, 15, 16, 17]. In these works, it is observed that the central factor for good control performance is forecast quality: the better the generation and demand forecasts, the more effective the control will be at minimizing curtailment.

Cai et al. [14] studied a multi-energy system combining photovoltaic generation, hydrogen storage, and power exchange with the electric grid. In their research, the authors propose a closed-loop predictive energy system, whose objective is to make the best possible use of local solar energy and thereby reduce power exchanges with the grid, that is, buying and selling less energy.

Given that photovoltaic generation is highly variable, a time series forecasting technique called EMD-KPCA-LSTM is employed. Empirical Mode Decomposition (EMD) decomposes the series into several components at different scales, separating fast and slow oscillations, among others. Kernel Principal Component Analysis (KPCA) performs dimensionality reduction, eliminating redundancies while retaining only the most relevant characteristics. Finally, the Long Short-Term Memory (LSTM) neural network learns the temporal dynamics and thereby generates the forecasts. In summary, this modeling approach first decomposes the photovoltaic series into components, then compresses the information, and finally uses the LSTM to produce the required forecasts.

The experiments showed that the EMD+KPCA+LSTM combination outperformed the other models tested (LSTM and EMD-LSTM). These results reinforce that good preprocessing improves the forecasting stage. The predictive controller solved a dispatch optimization problem at each instant over a 24-hour horizon, continuously updating via feedback. In case studies using real data from China, an increase of 13.71% in local photovoltaic energy utilization and a 42.59% reduction in grid interaction were observed; in other words, the system began to rely more on its own solar energy and less on the electric grid.

Shabbir et al. [15] analyzed low-voltage residential networks with distributed solar generation. When photovoltaic penetration is high, technical problems can occur, such as overvoltage, line overload, and reduced hosting capacity of the grid.

Rather than physically reinforcing the grid infrastructure by replacing cables or transformers, the authors pursue an intelligent control solution: a machine-learning-based strategy for managing the battery system, referred to as MLC-BESS. In this system, LSTM is used to forecast next-day photovoltaic generation, allowing for better planning of when to charge or discharge the battery in a more adaptive manner. In other words, the use of LSTM organizes battery usage to relieve grid stress without the need for infrastructure works.

The MLC method was compared to Basic Battery Control (BTC) and Analytical Control (ADC). The practical experiment was conducted during the period of highest solar generation on the grid, and MLC reduced the number of hours when voltage exceeded the limit: there were 30% fewer overvoltage hours than with ADC and 4% fewer than with BTC. In addition to the technical benefit, an economic benefit

was observed: residential consumers saved between 8% and 22% on their energy bills compared to the two benchmark strategies (BTC and ADC).

Mohandes et al. [16] developed a Renewable Energy Management System (REMS) to decide how to operate a hybrid plant with battery storage; that is, the focus is on finding the optimal hourly dispatch. The first innovation corresponds to a forecasting algorithm that relies on an ensemble of deep neural networks. The authors employed a Multiplicative Weight Update (MWU) method, which iteratively increases the weights of networks that forecast more accurately and reduces the weights of those that forecast poorly.

Syed et al. [17] addressed the smoothing of photovoltaic power and ramp rate control (how quickly power rises and falls), aiming to reduce the effects of solar intermittency on the grid. It was observed that the most commonly used smoothing filters presented a significant problem: as the smoothing level increased, these filters introduced substantial time delay, reacting belatedly to what was actually occurring in real time with photovoltaic generation. Due to this time delay, the system was unable to closely track the photovoltaic plant's actual output. Since the reference signal lagged the plant's actual output, the battery had to compensate for larger differences over longer periods. This would require a higher-capacity battery to perform the necessary smoothing and would lead to significant fluctuations in state of charge (SoC), with frequent charge-discharge cycles. These constant SoC fluctuations, with repeated cycling, accelerate battery wear, reducing its service life.

3.3. Adaptive control with Deep Reinforcement Learning (DRL)

There is a third set of articles, considered the most advanced, that employ Deep Reinforcement Learning (DRL). In these works, a control agent is trained and autonomously learns the best way to control the system, referred to as the optimal control policy. As it learns, the agent interacts with a simulated environment, tests actions, receives rewards and penalties, and thereby adjusts its strategy over time.

Thus, instead of programming fixed rules or relying entirely on forecasts, the agent experiments within simulations until it learns, through trial and error, how to make good control decisions. Therefore, compared to predictive control, one of the major advantages of DRL is that it does not require a detailed mathematical model of the system to be formulated: the agent learns behavior through interaction with the environment and therefore does not depend on extremely precise generation or demand forecasts over a fixed horizon. Instead, it observes the current state and adaptively decides what to do at that instant. Throughout training, the DRL agent ultimately incorporates uncertainty directly into the control policy itself, ceasing to treat uncertainty merely as a forecast error, and instead acting directly based on accumulated experience, responding to what the system presents at each moment.

The five articles in this category [8, 18, 19, 9, 20] represent the state of the art in DRL applied to energy systems, that is, the most advanced and recent developments in this field. These works are key examples illustrating how DRL has been evolving in the control of energy storage systems. Guedes Filho et al. [8] developed HybridEnergyEnv, a simulation environment designed to train and evaluate DRL agents for hybrid renewable energy systems. In this simulator, the hybrid plant is modeled realistically, including wind and solar generation and battery storage. Additionally, the environment also accounts for real-world conditions, such as charge and discharge efficiency, thermal limits, and battery capacity degradation modeled through the Rainflow method.

Zhang et al. [18] advanced through the use of multi-agent DRL, in which multiple agents cooperate to solve voltage and reactive power control problems in distribution networks with high penetration of distributed generation. Thus, the architecture proposed by the authors addresses the problem of maintaining voltage and reactive power under control in networks with high distributed generation, using multi-agent DRL, given that classical solutions are slow, depend on accurate models, and existing MADRL (Multi-Agent Deep Reinforcement Learning) solutions still face complexity and stability issues.

Prabawa et al. [19] created one of the most complete and capable frameworks among the articles analyzed. They proposed a two-stage energy management system for active distribution networks with connected Hydrogen Filling Stations (HFS). In Stage 1, a deterministic optimization model with hourly resolution is used to calculate setpoints, that is, reference values for voltage control devices.

This is the day-ahead planning layer: it decides, hour by hour, how this equipment will operate, thereby maintaining an adequate voltage profile and optimizing costs. In Stage 2, a DRL agent based on the Soft Actor-Critic (SAC) algorithm is used; this agent adjusts, nearly in real time, the dispatch of electrolyzers and fuel cells at the hydrogen stations every 15 minutes. Thus, it decides how much hydrogen will be produced or consumed and how much electrical power will be injected or absorbed. Therefore, Stage 1 is responsible for the optimal day-ahead planning of voltage equipment, while Stage 2 performs fine-tuning in real time, using DRL to control the safe operational limits of hydrogen storage, in response to actual grid and hydrogen supply conditions.

Li et al. [9] analyzed a system comprising a co-located photovoltaic solar plant and a battery storage system installed at the same site to operate in a coordinated manner. The objective was to establish a real-time bidding strategy in the energy market while simultaneously reducing solar generation waste, taking advantage of opportunities to profit by buying low and selling high. To enable these decisions, the authors represented the photovoltaic plant and the battery system, each, as a Markov Decision Process (MDP). At each instant, the agent observes the state and chooses an action, for example, when to bid in the market, subsequently receiving a reward in an uncertain environment. These two MDPs are solved using a DRL algorithm called Attentive Convolutional Deep Reinforcement Learning (AC-DRL), which employs attention mechanisms and convolutions to learn a smarter bidding policy over time.

Lin et al. [20] addressed the challenge of integrating renewable energy sources in the context of the Internet of Energy (IoE) and supported by 5G networks. In this type of configuration, numerous distributed sensors continuously collect data from the electric grid. Within this challenge, the authors have the specific objective of verifying the fragility of control systems to corrupted data. This corrupted data can arise from sensor failures, hardware defects, or even 5G signal transmission problems caused by interference, adverse weather, or packet loss.

3.4. Methodological evolution trajectory

In an initial stage of the analyzed articles, it can be observed that early research focused on the planning and economic sizing of storage systems, considering different combinations of renewable generation, batteries, and hydrogen. Ma et al. [13] developed a model to generate wind and irradiance output scenarios using WGAN-GP, explicitly addressing uncertainty and thereby optimizing costs, improving reliability, and exploring generation complementarity, given that it involves a wind-photovoltaic system with storage.

Shams et al. [5] also propose a model that simultaneously sizes and operates two types of storage: AWE and BESS. To do so, the authors employ a chain of techniques. First, they use Deep Learning-based forecasting to estimate the extent of renewable curtailment. Next, they fit a probability distribution function (PDF) to the forecast errors, thereby modeling the uncertainty associated with these errors. Based on this PDF, scenarios are generated, that is, several possible future realizations. These scenarios are then incorporated into a two-stage stochastic planning model: the first stage makes sizing and long-term decisions; the second stage determines hour-by-hour operation for each scenario, aiming to minimize annual cost, including penalties for curtailment.

The second stage consists of studies that integrate explicit generation and demand forecasting into the control decision process [14, 15, 16, 17]. In these works, photovoltaic generation and, in some cases, loads are forecasted using machine learning techniques or neural networks, and these forecasts feed rolling-horizon control schemes, either through strategies formally based on model predictive control or through anticipated dispatch policies. This coupling between forecasting and control results in greater local utilization of renewable energy and a reduced need for corrective actions, such as curtailment or grid reinforcements, although the reduction percentages vary depending on each study's configuration.

Conversely, the authors themselves indicate that forecast quality is a decisive factor in the strategy's overall performance: under high meteorological uncertainty, degraded forecast accuracy directly compromises the controller's ability to meet ramp-smoothing, demand-fulfillment, or overload-limitation targets. Furthermore, whenever model-based predictive control is adopted, as in [14] and in the hourly dispatch formulation of [16], sufficiently accurate mathematical models of system dynamics are required,

which tends to restrict the application of these approaches to contexts where physical behavior is well characterized and relatively stable over time.

The third and most advanced stage consists of model-free DRL approaches, in which control policies are learned directly from data and interaction with the environment, without relying on detailed mathematical models or exogenous forecasts of generation, demand, or prices. In this group, Guedes Filho et al. [8] use a single DRL agent (DDQN, PPO, or A2C) to dispatch a hybrid wind-solar-battery system in a high-fidelity OpenAI Gym environment, demonstrating that learned policies increase revenue and reduce curtailment with minimal analytical modeling requirements. Subsequently, Zhang et al. [18] extend the paradigm to a decentralized multi-agent scenario, using the PS-TD3 (Parameter-Sharing Twin-Delayed Deep Deterministic Policy Gradient) algorithm with parameter sharing among multiple cooperative voltage and reactive power agents in active distribution networks. Operational safety concerns are incorporated by Prabawa et al. [19], who propose a two-stage framework in which a continuous DRL agent is coupled with a plug-and-play safety module, ensuring that training and execution respect voltage and hydrogen state-of-health limits at filling stations.

In the context of real-time markets, Wang et al. [9] introduce Attentive Convolutional Deep Reinforcement Learning (AC-DRL), an architecture with attention mechanisms and multiscale convolutions that coordinates, across two decision processes, the bids of the solar plant and the battery, improving revenue and curtailment mitigation under highly volatile prices. Finally, Lin et al. [20] integrate Long Short-Term Memory (LSTM and Deep Deterministic Policy Gradient (DDPG into an L-DRL (LSTM+DRL) “bad-data-tolerant” scheme for optimal renewable accommodation in a 5G Internet of Energy scenario, using LSTM to filter and reconstruct states from corrupted measurements before the agent’s decision. Taken together, these works illustrate a trajectory moving from single DRL agents toward multi-agent, safe, attention-based, and bad-data-tolerant architectures, evidencing the growing maturity of DRL solutions and their adaptation to the practical requirements of power systems and real markets.

3.5. Comparative analysis of approaches

Table 1 presents a quantitative comparison of the main performance metrics reported by the analyzed articles, organized according to the method employed.

The analysis of the table above shows that ML-based algorithms are consistently superior, delivering better results in robustness and adaptability. Observing AC-DRL and L-DRL, it is evident that when attention mechanisms and data-treatment modules are incorporated, these architectures achieve significant performance gains over standard DRL algorithms. It is also noted that the two-stage framework with an adaptive safety module is the only one to achieve zero operational constraint violations during both training and execution, an indispensable characteristic for real power system applications.

To consolidate the argument for this study’s uniqueness, an additional analysis was conducted on a random sample of five recent systematic review articles, all conducted in accordance with the PRISMA protocol. The objective of this step was to verify whether the global secondary literature had already mapped the intersection between Artificial Intelligence, solar curtailment mitigation, and Pumped-Storage Hydropower Plants (PSHPs) within the context of the Brazilian electric power sector.

Table 2 presents the thematic coverage matrix of these systematic reviews.

Following the analysis of Table 2, it is observed that, among the selected systematic review articles, reviews related to ML in the electric power sector essentially address two themes: the use of artificial intelligence for solar generation forecasting [10] or the application of DRL to manage chemical batteries [11]. Thus, none of these systematic reviews examines DRL being used to decide, in real time, how to operate a pumped-storage hydropower plant. This gap is precisely the object of the present study, which seeks to understand it and propose pathways to address it.

In recent systematic reviews on pumped storage, such as [6], the focus is primarily on deployment and diffusion factors of pumped-storage plants — terrain and topography conditions, available infrastructure, investment costs, and PHES technological maturity — as well as the main drivers and barriers to their development. In line with this, [21] and [11] analyze the role of storage technologies (including PHES) in renewable integration, emphasizing economic viability, regulatory challenges, physical limitations,

Table 1
Quantitative comparison of the main performance metrics

Ref.	Approach	Main metric	Result (representative example)	Benchmark surpassed
[13]	Planning (SSA / WGAN-GP)	Curtailment reduction	Reduction between 3.6% and 14.7% relative to the no-storage case	Conventional sizing / no storage
[5]	Planning (GRU / stochastic model)	Curtailment recovery and annual cost	97% of curtailment recovered with AWE; annual cost 63.5% lower than BESS	Standalone BESS
[7]	Planning (ML / MILP)	Energy self-sufficiency / self-consumption	Self-sufficiency around 78% (optimized PV-BESS-EV scenario)	Operation without optimization / without ML pre-processing
[14]	Predictive control (MPC / EMD-KPCA-LSTM)	Curtailment reduction and grid exchanges	Local PV utilization +13.71%; grid exchanges -42.59%	MPC with conventional forecasting
[15]	Predictive control (MLC-BESS / LSTM)	Overvoltage reduction and consumer cost	-30% overvoltage hours vs. ADC; -4% vs. BTC; savings of 8–22% on bill	BTC and ADC
[16]	Predictive control (REMS / MWU ensemble)	Residual curtailment and system profit	Curtailment limited to 1.2–15%; profit +2.5% vs. basic forecasting	Control with single forecast (without MWU)
[17]	Predictive control (MR Filter)	Battery effort and ramp smoothing	Charge/discharge power -30.5%; SoC peak -19.1%	Traditional filters (MA, LF, SG, etc.)
[8]	DRL (PPO / A2C / DDQN)	Curtailment reduction and battery degradation	Curtailment -84.6% (DDQN); battery degradation -30.53% vs. PPO	No-storage scenario / rule-based control
[18]	Multi-agent DRL (PS-TD3)	Voltage control and power losses	Overvoltage -87.65%; voltage deviation -90.57%; losses -27.9%	Conventional TD3
[19]	Safe DRL (SAC + safety module)	Voltage/SoH violations, losses, and HFS profit	Zero voltage and SoH violations; losses 89.66 → 82.27 kW; profit 3.39 → 3.52 USD	SAC without safety module / MINLP
[9]	Attention-based DRL (AC-DRL)	Total revenue and response to curtailment events	Revenue +23% / +20% / +11% vs. DMPC/SMPC/MLP-DDPG; response to ~93% of curtailment events	DMPC, SMPC, MLP-DDPG
[20]	Robust DRL (L-DRL / LSTM + DDPG)	Renewable accommodation with corrupted data	Superior accommodation compared to DPG, with more evident gains after day 5	Conventional deterministic DPG

and technology readiness level, but without offering a specific synthesis of optimal real-time control algorithms for the hourly or minute-by-minute operation of large pumped-storage hydropower plants.

In the systematic reviews analyzed, renewable curtailment is primarily cited as an inefficiency that can be mitigated by integrating battery systems, particularly lithium-ion BESS, into solar-plus-storage arrangements [21] and [22]. However, these works do not specifically and thoroughly examine whether large pumped-storage hydropower plants could act as "hydraulic batteries" to store currently curtailed solar energy, nor do they systematically assess the technical and economic feasibility of this alternative compared to exclusively increasing battery capacity.

Finally, among the systematic reviews, there are no detailed case studies or analyses focused on the Brazilian context. When Brazil is mentioned, it appears only as an isolated reference within a list or citation [6], as a data point on maps or charts [10], or as a generic example of a developing country facing grid stability issues [22]. In summary, the Brazilian case is not addressed in detail in the mapped global reviews, so there is no substantive analysis of Brazil or even of the national electric power system.

Table 2

Thematic coverage matrix of systematic reviews included in the complementary contextual analysis.

Authors	Review focus	ML / DRL	Solar ment	curtail-PSHP / storage	Real-time opera- Brazil tion
Ali et al. (2021)	Global drivers and barriers for PSHP/PHEs deployment.	Not addressed.	Not addressed.	PHEs as large-scale storage; planning and deployment rather than intelligent operation.	Not addressed. Global perspective only; no Brazilian case study.
Obakhume & Opatola (2025)	Storage and smart grids for renewable integration, forecasting, and optimization.	General references for forecasting and optimization in VPP and DR; management; no specific DRL models.	ML/RL Indirectly for cussed through variability in DRL not a focus.	dis- PSHP/PHEs listed with batteries and hybrid age; no specific dispatch/control analysis.	Conceptual near-real-time operation in smart grids, VPP, and DR; no detailed AI-control model.
Ikhsan et al. (2026)	AI/ML for PV generation and efficiency forecasting, emphasizing CNN-LSTM.	PV ML, DL, and CNN-LSTM; DRL not addressed.	PV forecasting; curtailment-mitigation focus.	Not addressed.	Nowcasting, intraday, and day-ahead forecasting; no control scheme.
Erdiwansyah et al. (2026)	Circular energy-storage systems for SoC/SoH, control, ESS optimization, and life-cycle sustainability.	ML, DL, and DRL for SoC/SoH, control, ESS optimization, and life-cycle management.	Not specifically addressed; focus on renewable integration.	PHEs/PSHP as large-scale, long-duration mechanical storage; no unit-level dispatch analysis.	AI/DRL-based digital-twin real-time ESS/EMS control.
Dairo (2023)	Solar-BESS integration for resilience and reliability in distribution networks.	No AI/DRL; classical simulation and evaluation models.	BESS and grid resiliency; not a primary objective.	BESS only; PSHP not addressed.	Planning and operational assessment; no AI-based real-time control.

4. Concluding

When examining the set of articles studied, it is evident that the use of artificial intelligence, particularly ML, is a natural and necessary step toward controlling hybrid energy storage systems. First, a significant improvement arises from incorporating uncertainty in irradiance, demand, and price. Accounting for this uncertainty already at the planning stage, and thereby improving forecast quality, yields concrete benefits. In the studies analyzed, curtailment reductions ranging from approximately 3.6% to 14.7% were observed in optimized scenarios, along with reduced operational costs associated with real-time control. It was further verified that DRL, through algorithms such as DDQN, PS-TD3, and AC-DRL, proved to be an effective strategy for handling solar generation variability, outperforming traditional deterministic methods. DRL demonstrated the ability to eliminate voltage violations, reduce battery aging by up to 30%, and increase revenue, all without relying on rigid mathematical models, as the agent learns dispatch policies directly through trial and error by interacting with the environment.

Conversely, a scientific gap becomes apparent when comparing this review with other, more recent global systematic reviews. Most of the current literature focuses on two fronts: optimizing BESS in microgrids and isolated forecasting applications, such as generation or load forecasting. As a result, the potential of PSHPs as an ML-managed flexibility solution has been largely overlooked. No studies were found that applied ML specifically to PSHP operation to mitigate curtailment in large-scale interconnected systems, such as the Brazilian SIN. It is thus evident that while numerous studies focus on batteries and forecasting, there are almost no applications that combine DRL and PSHP in real-world large-scale systems.

Overall, the research questions reveal that the literature is relatively mature in AI-supported planning, forecasting, battery management, and real-time control of hybrid renewable energy systems. However, the evidence remains insufficient regarding the use of ML or DRL for the operational dispatch of PSHPs aimed specifically at mitigating solar curtailment in large interconnected power systems. This limitation is even more pronounced for the Brazilian National Interconnected System, for which no directly

applicable study was identified.

To contribute to the energy transition while preserving grid stability, it is important to develop and test ML agents to operate PSHPs. When analyzing the Brazilian context specifically, it is worth highlighting that regions with high photovoltaic potential could benefit from treating curtailment as a strategic asset. Thus, rather than wasting solar energy, DRL-controlled PSHPs would be capable of storing it during periods of surplus, thereby helping to reduce net-load ramps at the end of the day and increasing the effective use of clean energy. Accordingly, it is proposed that future work develop simulations and practical applications using these advanced DRL architectures to fill the identified gap and directly contribute to the modernization of the country's energy management.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly for grammar and spelling checks, paraphrasing, and rewording. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the publication's content

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