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Research Article

The Role of Mechanical Energy Storage Systems Based on Artificial Intelligence Techniques in Future Sustainable Energy Systems

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Abstract: The utilization of fossil fuels has played a substantial role in climate change and the progression of global warming. Consequently, there is an increasing demand for environmentally sustainable and renewable alternatives to address these issues. It is widely acknowledged that renewable energy resources represent the optimal choice for replacing fossil fuels in the foreseeable future. In this context, mechanical energy storage systems (MESS) continue to present substantial challenges to smart power grids (PGs). The MESS model can be purposefully designed to offer exceptional flexibility to smart PGs engaged in the intricate task of balancing energy resources and demand loads. MESS not only holds the potential for significant economic advantages but also ensures the reliability of smart PG supplies while delivering sustainability and maintaining a high level of power quality. Furthermore, it enables electrical grids to fully harness the benefits of a potent combination of distributed renewable energy resources (RER). The primary goal of this article is to facilitate the adoption of innovative MESS technologies that synergize with improved efficiency, energy conservation, and rapid response capabilities. The integration empowers smart PG to effectively employ intelligent operations management techniques. Thus, the utilization of artificial intelligence (AI) techniques in the smart PG domain is progressively manifesting its importance including Expert Systems, Supervised learning, Supervised learning, Reinforcement Learning, and Ensemble methods. This comprehensive survey provides a systematic analysis of the existing research endeavors employing various prevalent AI techniques in load forecasting, PG stability assessment, fault detection, and addressing security concerns within smart PG. Additionally, it delineates forthcoming research challenges that necessitate attention to fully actualize AI techniques in the creation of authentically smart PG systems. Ultimately, this survey underscores the potential for applying AI to tackle issues within smart PG systems, underscoring that the incorporation of AI techniques has the potential to significantly elevate and enhance the reliability and resilience of these smart PG systems.

Keywords: Compressed-Air Energy Storage, Pumped Hydro Energy Storage Systems, Flywheel Energy Storage Systems; Artificial Intelligence Techniques; Smart Power Grids.

1. Introduction

The injection of carbon dioxide (CO_2) into the Earth's subsurface has been a practiced technique since the 1970s, and the establishment of dedicated CO_2 storage, where the primary intent is the containment of CO_2 rather than its utilization for enhanced oil recovery, has been underway since 1996. Presently, there exist seven dedicated CO2 storage sites on a commercial scale, with over a hundred others in various stages of development. In the IEA Net Zero Emissions by 2050 Scenario, commonly referred to as the 'Net Zero Scenario' an impressive 5.9 gigatons (Gt) of CO2 are envisioned to be captured and securely stored by the year 2050. Achieving this target necessitates a substantial amplification of dedicated CO2 storage infrastructure, considering that the current annual injection of CO$_2$ into dedicated storage facilities amounts to approximately 10 million tons (Mt) per year [1-3].

Energy storage systems (ESSs) are undergoing rapid expansion within electricity systems worldwide, driven by countries' efforts to enhance their energy security [4,5]. Electrical utilities are increasingly relying on the effective deployment of flexible resources, including robust grid infrastructure, interconnections, demand-side measures, affordable energy storage solutions, and dispatchable power supplies [6]. Consequently, numerous nations have adeptly and securely incorporated significant portions of variable renewable energy sources (VRE) into their electricity generation portfolios, marking a pivotal milestone in the pursuit of sustainable energy practices. Increasing demand for energy and concerns about climate change stimulate the growth in VRE. According to the IRENA's statistics [7], the world's total installed capacity of renewable energy increased from 1,223,533 MW in 2010 to 2,532,866 MW in 2019, and over 80% of the world's electricity could be supplied by renewable sources by 2050.

Furthermore, the incorporation of ESS has ushered in a swift, user-friendly, and highly efficient solution to address the challenges of integrating RER into smart power grids [8,9]. Within the realm of energy storage, electrical energy undergoes conversion into alternative forms that can be stored for future utilization. To delve deeper into this subject, it's essential to note that ESS can be classified in various ways by the nature of the stored energy (electrical, mechanical, chemical, thermal, etc.), the storage duration (long-term or short-term), or other pertinent criteria such as capacity cost, efficiency, and environmental impact [10-14]. Figure 1, for instance, categorizes energy storage based on the type of energy they store.

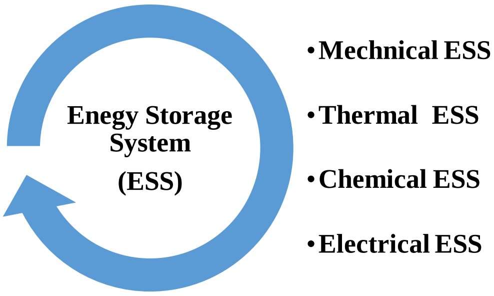

Figure 1. Categorization of ESS based on the type of energy they store.

Mechanical Energy storage system, particularly Pumped Hydro Storage system (PHSS), boasts a rich historical legacy as a crucial tool for grid dispatching and peak load management. In the past, coal and gas reserves were the primary forms of storage used to facilitate the flexible dispatch of energy. However, as technological advancements unfolded, a diverse array of viable energy storage solutions emerged within the market. In this context, the China Energy Storage Alliance disclosed that China had already operationalized 118 energy storage projects. Collectively, these projects contributed to an installed capacity of 105.5 MW, showcasing an impressive annual growth rate of 110% from 2010 to 2015. This remarkable growth trajectory indicates a projected capacity of up to 24.2 GW (excluding PHS) and 40 GW (inclusive of PHS) by the year 2020 [15].

Mechanical energy storage system (MESS) has grown in importance in light of recent CAES concepts and compressed air storage (CAS) options, meticulously assessing their merits and limitations [16]. The proposed model [17] is formulated as a mixed-integer nonlinear problem, which is solved by the CPLEX solver of the GAMS software. Employing the presented model in the 6-bus test system demonstrates the efficacy of the proposed model. Simulation results show that considering restrictions on reserve deliverability across multiple hours lessens the total reserve by 22.75 MW and increases the operation cost by $438.26. In this regard, Flywheel energy storage systems (FESS) are increasingly being considered as a promising alternative to electrochemical batteries for power grid (PG) utility applications. therefore, focuses on developing a bottom-up techno-economic model to design system components and to evaluate the total investment cost and levelized cost of storage of flywheels with a capacity of 20 MW/5 MWh for frequency regulation. Two rotor configurations were considered:

composite rotor flywheel and steel rotor flywheel [18]. The total investment costs of the composite rotor and steel rotor FESSs are $25.88 million and $18.28 million, respectively. The corresponding levelized costs of storage are $189.94/MWh and $146.41/MWh. The model results are highly sensitive to the cost of the rotor material, discount rate, factor of safety, number of cycles per year, and tensile strength of the rotor material. The ranges obtained in the uncertainty analysis for the levelized cost of storage are $122.08-$253.52/MWh and $108.63-$187.64/MWh for the composite rotor and steel rotor flywheel storage systems, respectively.

The MESS is intended to provide an extremely flexible facility to the electrical grids that engage in harmonizing energy resources and demand loads in order economic impact, and secure electric-power supplies to effectively deliver sustainable and high power quality. Moreover, the electrical grids can begin to derive full benefits from a powerful combination of distributed renewable energy resources (RER). The contribution of this article [19] aims to involve implementing innovative MESS technologies that work hand in hand with greater efficiency, efficiency, and rapid response to integrate electrical grids cope with intelligent techniques such as particle swarm optimization (PSO), artificial neural network (ANN), and fuzzy logic controller (FLC). These intelligent controllers are being actively considered to regulate the power from MESS technologies to integrate within the PGs.

The integration of Mechanical energy storage systems (MESS), such as Compressed air energy storage (CAES), Flywheel energy storage system (FESS), and Pumped hydro energy storage systems (PHESS) with smart power grids (PGs), offers a transformative solution to address the challenges of renewable energy intermittency and grid management complexities. MESS enables energy generation and consumption decoupling, ensuring economic savings, secure power supplies, and high power quality. Simultaneously, the integration of Artificial Intelligence (AI) techniques, including Expert Systems, Supervised learning, Supervised learning, Reinforcement Learning, and Ensemble methods, empowers smart PGs with data-driven decision-making capabilities, facilitating accurate load forecasting, grid stability assessment, fault detection, and cybersecurity. However, technical challenges such as data management, security, and AI algorithm transparency must be addressed. The synergy between MESS and AI holds great promise for optimizing PG operations, reducing costs, and enhancing reliability, with future research focusing on algorithm interpretability and the prediction of consumer behavior for revolutionizing demand-side management. While the rest of the article is structured as follows: the integration of mechanical energy storage system with the smart PGs listed in **Section 2**. The artificial intelligence techniques for smart PG is presented in **Section 3**. **Section 4** investigates the technical challenges of artificial intelligence in smart PG. The directions and prospects of artificial intelligence in smart PGs are demonstrated in **Section 5**. Finally, **Section 6** deals with the conclusion.

2. Integration of MESS with the Smart PGs

To establish the context for the subsequent sections, it is imperative to categorize the various types of Mechanical Energy Storage Systems (MESS) based on their fundamental operational principles. They encompass Compressed-Air Energy Storage (CAES), Pumped Hydro Energy Storage Systems (PHESS), and Flywheel Energy Storage Systems (FESS), as illustrated in Figure 2.

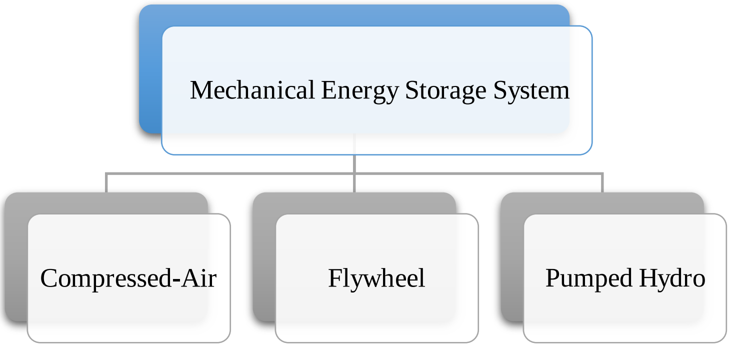

Figure 2. Classification of MESS.

A. *Compressed-Air Energy Storage*

The foundational principles of energy storage via compressed air can be traced back to the 1940s when F.W. Gay submitted a pioneering project titled 'Means for Storing Fluids for Power Generation.' During that era, Mr. Gay was granted a patent for this innovation by the United States Patent Office. Over subsequent decades, the United States and Germany have operated two traditional Compressed-Air Energy Storage (CAES) plants, boasting power generation capacities of 110.0 MW and 321.0 MW, respectively. Until the late 1960s, Germany led the way in advancing CAES technology in a specific region, harnessing the immense potential of underground salt domes to achieve this objective. Eventually, the utility company Nordwest-Deutsche Kraftwerke (NKW) determined that the Energy Transfer Storage System should be established in Huntorf [20-22].

Subsequently, Brown, Boveri & Company (BBC) designed the turbine air storage peaking plant technology, which served a crucial role in achieving peak-load capacity [23]. The United States Department of Energy (DOE) embarked on a comprehensive CAES (Compressed-Air Energy Storage) reform program, which unfolded at the Pacific Northwest National Laboratory during the late 1970s and extended into the early 1980s [24,25]. This scientific endeavor revolved around two primary objectives: (i) elevating the stability standards governing CAES operational requisites and (ii) exploring the viability of second-generation CAES, famously known as adiabatic CAES (A-CAES), with the overarching goal of curbing the consumption of petroleum-based fuels for combustion. Figure 3 illustrates various CAES concepts, distinguished by their idealized change of state, encompassing D-iabatic D-CAES, adiabatic A-CAES, and isothermal I-CAES.

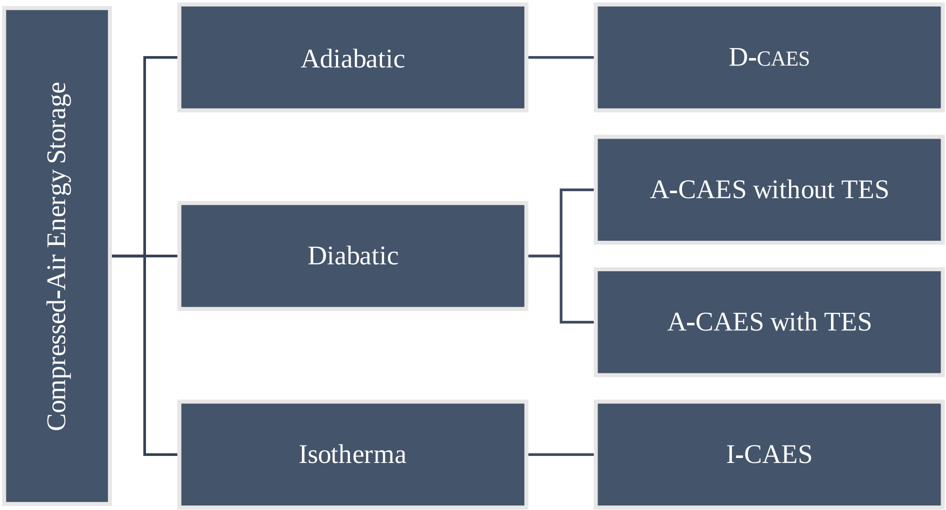

Figure 3. CAES concepts are classified by their idealized change of state: D (diabatic), A (adiabatic), I (isothermal)-CAES).

As a consequence, in the United States, the Electric Power Research Institute (EPRI) assumes full responsibility for the advancement of second-generation CAES technologies, including adiabatic CAES, isothermal CAES (I-CAES), and hybrid CAES systems. Figure 5 elucidates the architectural framework of an isothermal CAES system integrated with a wind turbine. Notably, the Pacific Northwest National Laboratory (USA) has been actively investigating A-CAES as a promising technology, ideally suited for various applications. Simultaneously, the EPRI identifies the hybrid CAES plant coupled with a thermal energy storage system (T-ESS) as the most promising second-generation solution. Grid-scale electrical energy storage primarily sources its power from CAES systems with a capacity of up to 400.00 MW. Table 1, shows the summarized recent studies in CAES.

Table 1. The summarized recent studies in CAES

Ref.	Year	Type of MESS	Summarized
[26]	2023	CAES	▪ A comparison between the daily and weekly circulation periods in the dome-shaped and horizontal aquifers showed that the daily circulation has an efficiency advantage at the same energy storage scale, and the energy recovery efficiency of the horizontal aquifer in the weekly circulation can reach approximately 74% of that of the dome-shaped aquifer. ▪ A constant flow rate injection/production gas daily cycle mode was investigated, and the results showed that this mode has higher energy recovery efficiency than the constant pressure cycle mode, and the horizontal aquifer can reach 88.39% of the efficiency of the dome-shaped aquifer.
[27]	2023	CAES	▪ The exergy analysis of the system demonstrated that the solar subsystem and SRC had the highest contributions to total exergy destruction. A comparative case study was conducted on Isfahan, Bandar Abbas, Mashhad, Semnan, and Zanjan in Iran to evaluate the performance of the proposed system at different ambient temperatures and irradiance levels during the year. ▪ The contradictory objective functions of the system included exergy efficiency maximization and cost rate minimization. The optimal Exergy round trip efficiency and cost rate were found to be 29.25% and 714.25 ($/h), respectively.
[28]	2023	CAES	▪ The improvement in flexibility was quantified by the additional profits gained from the integration. Polish day-ahead electricity prices were used as a measure of remunerating flexibility. Two models were developed in the Python computer programming language: a thermodynamic one and an economic one. ▪ The former was built without the use of flowsheeting software or purpose-built industry-specific tool. The latter was implemented within the frame of the PuLP library and solved using its default solver (CBC). Utilizing mixed integer linear programming (MILP) optimal generation schedules and maximum profits were found for three cases: an independent operation of the CCGT, an integrated CCGT-CAES plant, and an integrated CCGT-ES plant with 81% storage efficiency.
[29]	2023	CAES	▪ This paper discusses the design of a heat storage unit with integrated heat exchangers (TES + HX), which is intended to work in a CAES system. ▪ A medium-scale, medium-duration CAES system (250 kW/1MWh) is used as a case study. The heat storage subsystem comprises a packed-bed thermal store, three air-to-air heat exchangers, and an ambient pressure air blower. Combined, this subsystem has an approximate cost of £147k and achieves an efficiency of ~89 %, which translates into a levelized cost of ~48.5 £/MWh. ▪ An integrated TES + HX unit can achieve a levelized cost of ~35 £/MWh. The unit has an estimated cost of £38.5k and achieves an overall roundtrip exergy efficiency of ~91.8 %.
[30]	2023	CAES	▪ The objective is to deal with power failures and interruptions in power grids that have a high level of renewable resource penetration while reducing the emissions produced by CAES systems. ▪ The suggested system is then optimized using the gray wolf algorithm to determine the optimal way to balance thermodynamic performance with economic and environmental factors. This system's exergy round trip efficiency is 71.03%, its total cost is 34.07 $/h, and its pollution rate is 0.184 kg/kWh

Much of the current literature [31] on CAES pays particular attention to the total energy demands. Moreover, the present article indicates that the compressed air as a part of the Brayton cycle covers the total energy demands of hydrogen compression and cooling. In terms of storage efficiencies, the energy and exergy efficiencies for the charging period are found to be 72.65% and 71.52%, while they become 35.3% and 35.24% for the discharging period, respectively. The overall system energy and exergy efficiencies are calculated to be 35.00% and 34.38% for a period of 12 h charging and a period of 6 h discharging. In addition to that, more recent attention [32] has centered on the provision of A-CAES based on the actual engineering of power plants, real, unavoidable, and hybrid thermodynamic cycles, and conventional and advanced exergy analyses. In this regard, the avoidable exergy destruction indicated the highest potential for improvement of the third-stage heat exchanger (HEX3) contributing to 13.15 % of the total avoidable exergy destruction of the system; therefore, HEX3 has the highest optimization value. In addition, the second-stage heat exchanger (HEX2) and first-stage heat exchanger (HEX1) also exhibited higher potential for improvement.

Research [33] in this area has shown that the system makes full use of low-grade compression heat while consuming the generated carbon monoxide to output hydrogen to the outside. By constructing a systematic thermodynamic model of the system, the effects of the key parameters on the system performance were investigated in depth. The article also showed that the energy efficiency and exergy efficiency of the system can reach 85.71 % and 80.94 %, respectively. When the suction pressure of the water-air coexisting tank is increased from 5 atm to 20 atm, the air storage mass increases by 33.96 %. At the cracking temperature of 708 K, the energy storage density can reach 12.37 kWh/m3, the hydrogen production mass is 3113.38 kg, and the relative energy saving rate is 54.38 %.

In this direction, recent research [34] has demonstrated that the thermodynamic model and wellbore model are constructed to evaluate the performance of the proposed system based on CAES. Besides that, the numerical results illustrated that the production temperature increases with the augment of the mass flow rate, but the increase of the recharge pressure has no obvious effect on the production temperature. In addition, the round trip efficiency of the system fluctuates between 48.59%~and 54.88%, which is much better than that of the traditional compressed air energy storage system (42%).

Existing research [35] recognizes the critical role played by integrating water-based carbon capture with an adiabatic compressed air energy storage system. The flue gas with a higher carbon dioxide concentration is employed as the working fluid of the adiabatic compressed air energy storage system (A-CAESS), and the flue gas's total pressure is raised by the compression train. Moreover, thermodynamic analysis was evaluated using steady-state mathematical models and thermodynamic laws. The calculated results of this article showed that the energy consumption of carbon capture is 354.23 kWh/t, which is significantly lower than amine-based capture technology (about 1000 kWh/t).

B. *flywheel energy storage system (FESS)*

Flywheel energy storage system (FESS) takes advantage of the possibility to store electrical energy as kinetic energy [36]. FESSs use electrical energy to accelerate or decelerate the flywheel, that is, the stored energy is transferred to or from the flywheel through an integrated motor/generator and power converter [37]. The rotating speed of the flywheel determines the amount of energy stored. Figure 4, presents the most critical mechanical part of the FESS, which is the bearing. Table 2, discusses in detail the suitable FESS. The overall bearings of the FESS are divided into two types: (i) mechanical bearings and (ii) magnetic bearings. Mechanical bearings have been successfully applied for low-speed FESS. These mechanical bearings can have their drawbacks by friction and require lubrication and maintenance [38]. More particularly, the variable reluctant machine (VRM), the induction machine (IM), and the permanent magnet machine (PMM) are utilized by FESS. Table 3, illustrates the summarized recent studies in FESS.

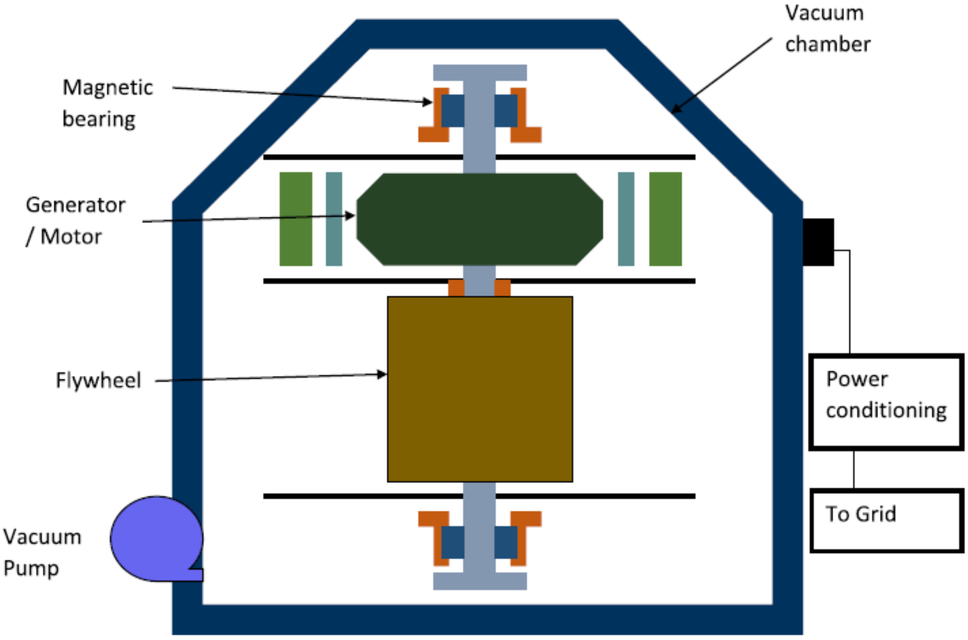

Figure 4. Structure of a FESS [36].

Table 2. The suitable FESS for smart PGs [19].

FESS	Asynchronous	VRM	PMM
power	High	Medium	Medium
Spinning losses	Removable by annulling flux	Removable by annulling flux	Non-removable, static flux
Efficiency	High	High	Very high
Control	Vector control	Synchronous: Vector Control. Switched: DSP	Sinusoidal: Vector control. Trapezoidal: DSP
Size	1.8 L/kW	2.6 L/kW	2.3 L/kW
Tensile strength	Medium	Medium	Low
Torque ripple	Medium	High	Medium (10%) Low
Maximum/base speed	Medium	High	Low
Demagnetization	No	No	Yes
Cost	Low	Low)	Low

Moreover, the design of the magnetic bearing allows FESS to work at peak efficiency and longer life-cycle, which has always been attracted by many academic types of research. Moreover, the composite materials can gain a competitive advantage over a high power density and its high-speed FESS up to 100,000 rpm by reducing the weight [39]. The power density of FESS can reach 5,000 kW/ m^3 and 80% to 95% of Cycle efficiency. Using equation (1) is to calculate the amount of stored energy by the FESS as follows.

$$E_{FW} = \frac{1}{2}\,\vartheta\,\omega^2 \tag{1}$$

Equation (1) is a clear indication that E_{FW} refers to stored energy by FESS. Both symbols of J and ω are the state of inertia as well as the angular velocity of the rotor. The increasing speed or even the state inertia are directly affected by enhancing stored energy of FESS, respectively. It is worth mentioning that the state of inertia relies on the specific form and mass (m) of FESS. Equation (2) presents the state of inertia (J).

$$J = \frac{1}{2}\,m\,r^2 \;or\; J = \frac{1}{2}\rho\,\alpha\,\pi\,r^4 \tag{2}$$

Where r refers to radius and α is related to length. The ρ indicates the mass density of FESS. Furthermore, the operation of FESS can be expressed as equation (3) by applying a mechanical equation.

$$\vartheta \frac{d\omega}{dt} = T_{em} - f_{\omega} \tag{3}$$

It is perfectly feasible to store more energy by taking into account the increase in disk radius or even by applying high-density material. Where T_{em} is noted as an electromechanical torque and f refers to the friction coefficient term.

Table 3. The summarized recent studies in FESS.

Ref.	Year	Type of MESS	Summarized
[40]	2023	FESS	▪ As different shapes of flywheels have different moments of inertia and energy storage efficiency, this study also examined the energy density of the FESS under different shapes and obtained the best-fit shape for the hydraulic power unit. ▪ A test platform is set up to verify the effectiveness of the proposed hydraulic drive system. Results show that the installed power is reduced by approximately 41.9 % and the energy consumption is reduced by 53 %, compared to the traditional hydraulic presses (HPs).
[41]	2023	FESS	▪ This paper proposes an impingement jet cooling structure with a rotating axis to facilitate the heat dissipation of FESS. The implications of the cooling medium, nozzle length, cavity zone diameter, and nozzle diameter of the impingement jet cooling structure on flow and heat transfer performance are studied by field synergy theory. ▪ The Nusselt number, friction coefficient, field synergy angle, comprehensive coefficient of heat transfer, and temperature field are analyzed. ▪ Heat transfer can be improved by decreasing the diameter of the cavity zone, lengthening the nozzle, and increasing the nozzle diameter. The pressure drop of the optimized structure is at least 62.48% less than that of the unmodified structure, while the temperature increase of the cooling medium is nearly 3.5 times higher.
[42]	2023	FESS	▪ The article demonstrated that a 40 % reduction in the operating pressure can reduce the flywheel surface temperature and wind loss by 20 % and 30 %, respectively. ▪ A partial vacuum environment can achieve better energy conversion efficiencies provided an appropriate bearing seal is achieved to maintain the pressure inside the housing. ▪ The investigated flywheel energy storage system can reduce the fuel consumption of an average light-duty vehicle in the UK by 22 % and decrease CO2 emission by 390 kg annually.
[43]	2023	FESS	▪ A FESS integration and sensitivity analysis performed on a 1MW wind power site with varying degrees of export limitation in place show that the site could generate an additional 6.1–38.5MWh over a year. ▪ Subsequent novel economic analysis of the installations showed that the system is economically viable across a wide range of scenarios, increasing the Net Present Value of the site by up to 1.25%. ▪ Finally, the performance of the FESS is compared to a Lithium-ion battery energy storage system, highlighting the novel contribution of using a flywheel for this application by showing the excessive cycling a BESS would experience and the knock-on effect this has on economic viability.
[44]	2023	FESS	▪ Experimental results show that the FESS can be applied to smooth high-frequency wind power output from wind power generation with relatively good results. ▪ The FESS using the model predictive control (MPC) system is more effective in smoothing wind power fluctuations at short time scales due to the fast response

			characteristics of the FESS and the precise control characteristics of the MPC control system.
[45]	2023	FESS	▪ FESS is applied to compensate for the transient power changes, mitigate load fluctuations, and maintain the voltage of the shipboard direct current (DC) bus. ▪ The coordinated control strategy of the micro gas turbine, FESS, and load system is designed. The mitigation effects of FESS on marine gas turbine DC Microgrid under high-power load mutation are explored by performing simulation with sudden load changes of 25%, 50%, and 75% rated power and comparing the performance with and without FESS.

Recently investigators [46] have studied the effects of FESS concerning its main components and applications. The main applications of FESS in power quality improvement, uninterruptible power supply, transportation, renewable energy systems, and energy storage are explained, and some commercially available flywheel storage prototypes, along with their operation under each application, are also discussed. Moreover, FESS offers the unique characteristics of a very high cycle and calendar life the best technology for applications that demand these requirements. A high power capability, instant response, and ease of recycling are additional key advantages.

In recent years, different approaches [47] have tried to account for the FESS that can be applied from very small micro-satellites to huge PGs. There are three main devices in FESS, including machine, bearing, and power electronic interface (PEI). Furthermore, the advantages and disadvantages of all of them have been presented. In addition, a brief review of new and conventional power electronic converters used in FESS has been discussed. The article [48] was carried out on studies that FESS is an energy conversion device designed for energy transmission between mechanical energy and electrical energy. Moreover, there are high requirements on the power capacity, the charging efficiency, and the output precision of FESS. Active magnetic bearings are used to suspend the flywheel (FW) rotor of the FESS in air to eliminate friction. A high rotating speed of the flywheel can increase the power capacity but it also increases the disturbance load torque on the FW rotor.

The article [49] investigated the design, optimization, and analysis of FESS used as a dynamic voltage restorer. The first purpose of the article was to design a flywheel with a natural resonance frequency outside the operating frequency range of the FESS. The matrix converter needs a special motor/generator design, because of the voltage utilization ratio of the matrix converter. Therefore, a permanent magnet synchronous motor (PMSM) being compatible with the matrix converter voltage level was designed and optimized. The motor was optimized to achieve low torque ripple and as high torque as possible by using a multi-objective optimization algorithm. Input/output voltages of the FESS are analyzed for PG interruption and 50% voltage sag operation conditions. The frequency analysis study was performed by using SolidWorks, the PMSM was designed and optimized by using MAGNET-Infolytica, and all the other results were performed by using MATLAB-Simscape.

C. Pumped hydro energy storage system (PHESS)

PHESS represents a sophisticated infrastructure designed to harness electrical energy by capitalizing on the potential energy stored in water. This process entails employing an electric pump to transport water from a lower reservoir to an upper water body via a conduit. Subsequently, gravity allows this stored water to flow through a hydro turbine, descending from a higher elevation to a lower one. It is imperative to acknowledge that for the successful implementation of pumped hydro energy storage systems, certain prerequisites must be met [50,51]. Moreover, the extent to which such energy storage sources can contribute to the energy landscape of developing nations hinges significantly on the availability of suitable sites and access to water resources. When these prerequisites are met, PHESS emerges as an exceptionally well-suited choice for renewable energy storage and integration into the PG [52-53]. In stark contrast to alternative energy storage methods, PHESS systems exhibit noteworthy efficiencies, typically falling within the range of 70% to 80%, with a customary capacity spanning from 1000.0 MW to 1500 MW [54,55].

It's worth noting that Europe boasts a cumulative PHESS capacity of approximately 55.0 GW, whereas the global capacity stands at a substantial 170.0 GW. PHESS systems demonstrate remarkable robustness and seamless integration into electrical grids, making them a pivotal consideration when evaluating the impact of energy storage technology on grid infrastructure. Table 4, summarizes recent studies in PHESS. The installed capacity P (kW) of a pumped-storage plant is measured from the next equation (4).

$$P = \rho \times g \times Q \times (H - \Delta H) \times \eta \tag{4}$$

Where P is known as the density (kg/m^3) of water, g is referred to as acceleration due to the gravity (mm^2). Moreover, Q presents the discharge (m^3/s), and H shows the head (m). Then, ΔH is well-known as the loss of hydraulic head. The term η is called the efficiency of the generator.

Table 4. The summarized recent studies in PHESS.

Ref.	Year	Type of MESS	Summarized
[56]	2023	PHESS	▪ This article investigates the inner flow characteristics in the guide-vane region of a prototype system with the horizontal shaft in the optimal pump mode. ▪ A new phenomenon, partial flow separation, is discovered. The most intuitive feature of partial flow separation is that large-scale separation vortices in the guide-vane region are concentrated in the top passages of the antigravity part, while the bottom passages demonstrate good through-flow capacity.
[57]	2023	PHESS	▪ Geographic information system and analytic hierarchy process (GIS-AHP) pumped hydro energy storage System (PHESS) site selection method developed. Moreover, the method identified 14 potentially feasible sites in North Queensland, Australia. ▪ LCOE ranged between 0.04 AU$/kWh and 0.27 AU$/kWh for the base case scenario.
[58]	2023	PHESS	▪ The trend of PHES potential capacity showed a similar pattern, which had slopes of 5548.5 ± 69.2 GWhyr^{-1} and −238.1 ± 90.4 GWhyr^{-1}, with 1995 serving as the turning point. ▪ An ever-accelerating rising trend of future PHES potential is predicted. Compared with the reference period, the mean PHES potential density will increase by 21.7 %, 23.2 %, 23.8 %, and 25.4 % in the near, short, medium, and long terms.
[59]	2023	PHESS	▪ The article aimed at the fundamental principles, design considerations, and various configurations of PHESS, including open-loop, closed-loop, and hybrid designs. ▪ The article highlighted the crucial role of PHESS in integrating renewable energy sources, mitigating peak load demands, and enhancing power grid stability.
[60]	2022	PHESS	▪ This study investigated the frequency and power balance of an isolated Microgrid system, by including storage systems (battery and pump-hydro). ▪ Realistic data for wind and solar sources are used for the optimal tuning of the proportional-integral controller, using the integral of the absolute error criterion multiplied by time, with a Quasi-Newton method. ▪ Simulation studies have been carried out, to investigate the performance of the Microgrid system, by including the hydroelectric power plant system with pump storage for 24 h, under various operating conditions.
[61]	2023	PHESS	▪ This paper introduced a two-step site selection concept, including a screening assessment followed by a comprehensive assessment, to determine suitable locations for underground PHESS. ▪ The screening indicated in the screening assessment comprises geological features, mine water disasters, and minimum installed capacity, while the analytic hierarchy process is applied in the comprehensive assessment. ▪ Coal mines in Henan Province are preliminarily screened through the screening assessment and the potential for underground PHESS is thoroughly investigated. ▪ By consuming surplus wind and solar power, underground PHESS can reduce 4.68 × 105 tonnes of carbon dioxide (CO2) emissions.

A fundamental aspect of PHES is a matured technology for large-scale storage applications, that can absorb surplus electrical power from the network system, thus making it a relatively flexible cost-effective solution in comparison to other technologies such as batteries and power-to-X or interconnections [62]. Moreover, another study [63] evaluated the potential benefit of retrofitting existing conventional cascade hydropower stations (CCHSs) with reversible turbines to operate them as PHESS. The study also examined the energy generation and storage problem for a CCHS with two connected reservoirs that can be transformed into the PHES system in a market setting where the electricity price can be negative. The article also formulated this problem as a stochastic dynamic program (SDP) under uncertainty in the streamflow rate and electricity price.

PHSS [64] is a dominant feature of the different possible scenarios for the replacement of light fuel oil (LFO) thermal power plants connected to the power grid in northern Cameroon by renewable energy plants. Several scenarios such as the combination of solar photovoltaic (PV) with a pumped hydro storage system (PHSS), Wind and PHSS, and PV-Wind-PHSS have been studied. The selected scenarios are evaluated based on two factors such as the system's total cost (TC) and the loss of load probability (LOLP). The metaheuristics such as the non-dominated sorting whale optimization algorithm (NSWOA) and non-dominated sorting genetic algorithm-II (NSGA-II) have been applied under MATLAB software. However, the total cost in the PV-PHSS, Wind-PHSS, and PV-Wind-PHSS scenarios with NSWOA is, respectively, 1%, 6%, and 0.2% lower than with NSGA-II. According to NSWOA results, the total cost for the PV-Wind-PHSS scenario at LOLP 0% is 4.6% and 17% less than the Wind-PHS and PV-PHSS scenarios, respectively.

The subject of PHES [65] has received considerable critical attention using a daily mean reverting jump diffusion stochastic model of electricity prices in a risk-neutral world. The study showed that the income with this strategy under uncertainty may be insufficient compared to investment costs. Moreover, the strategy does not usually provide proper guarantees as regards SoS at times of high electricity demand. Besides that, the technical characteristics of PHESS such as the maximum upper, and lower reservoir volume are highly significant. PHESS profitability can be improved under a generating company (GENCO) strategy coordinated with a wind farm and if the avoided CO2 emissions are taken into account. The article [66] has long been a question of outstanding concern in hydropower generation. The article also an emphasis on installations in the Middle East and North Africa (MENA) in terms of available capacity as well as past and future developments and expansions. A discussion is presented on a project taking place in the United Arab Emirates (UAE) in the Hatta region, which has a water reservoir that would be fit for utilization for pumped hydro storage applications. Once the project is commissioned in 2024, it provided an estimated 2.06 TWh per year, helping the UAE achieve the goal of relying on 25% renewable energy resources in their energy mix by 2030. These results were obtained by using EnergyPLAN software to project the effect of utilizing various energy resources to face the expected demand of ~38 TWh in 2030.

3. Artificial Intelligence Techniques for Smart PGs

Due to the swift evolution of the smart PGs, an increasing distribution of components within the power grid (PG) within mechanical energy storage system (MESS), including elements like smart PGs metering infrastructure, communication networks, distributed energy resources, and electric vehicles, have become closely interwoven into the power grid's [67,68]. This integration forms an extensive PG that relies heavily on an intricate communication infrastructure. In addition to that, these components collectively generate substantial volumes of data, which serve as the backbone for automating and elevating the smart PG's operational efficiency [69-73].

This data is instrumental in supporting a wide array of critical applications, such as distributed energy management, predictive system state forecasting, fault detection, and cybersecurity measures. These AI methodologies have emerged as a compelling solution to tackle the complexities inherent in smart PGs [74-80]. By harnessing large-scale data, AI approaches offer the potential to substantially enhance the performance and functionality of smart PGs, addressing multifaceted challenges in this rapidly evolving landscape.

AI techniques within the context of the smart PQ integrated with MESS can be broadly categorized into several key areas:

- Expert Systems (ES): These involve employing human expertise within a computational framework to tackle specific problems.
- Supervised Learning: This AI paradigm revolves around the study of input-output mappings to make predictions for new inputs. It's a well-established method for training AI models.
- Unsupervised Learning: Falling under the machine learning umbrella, unsupervised learning utilizes unlabelled data to uncover patterns, similarities, and differences within the dataset.
- Reinforcement Learning (RL): In contrast to supervised and unsupervised learning, RL introduces intelligent agents that make decisions to maximize cumulative rewards. It focuses on learning through interactions and decision-making.
- Ensemble Methods: These methods amalgamate outcomes generated by multiple AI algorithms to mitigate the limitations of individual algorithms, ultimately yielding enhanced overall performance.

A. *Expert System*

The expert system (ES), as illustrated in Figure 5, represents the earliest generation of intelligent systems. It was developed to replace human experts within specific domains, offering solutions to particular problems using Boolean logic. Even today, many challenges within the smart PG integrated with the MESS domain, including fault diagnosis, intelligent control, and energy router decision-making, continue to rely on ES techniques [81-84]. The ES operates by incorporating domain knowledge gathered from experts in the field. This knowledge, combined with relevant databases, constitutes the knowledge base, which serves as the central component of the ES.

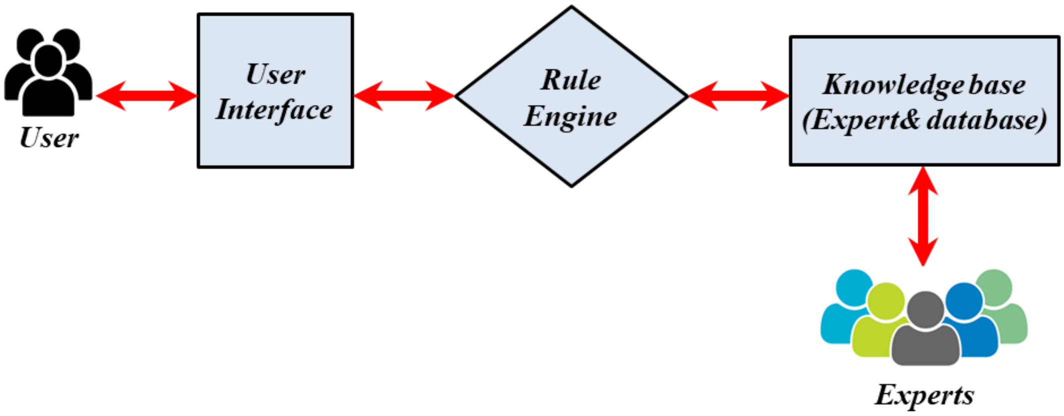

Figure 5. The diagram of an expert system.

Within the knowledge base, rules are formulated in the form of if-then statements, linked by logical operations [85-87]. This knowledge can be sourced directly from domain experts or extracted from research findings. The ES deduces solutions to problems by evaluating if-then rules against user-provided input data, which interfaces with the knowledge base via an intermediary rule engine.

B. *Supervised learning*

Supervised learning, a machine learning task, involves creating generalized hypotheses based on input and output data. This is achieved by training the system with labeled input-output pairs from external sources. Following training, the resulting mapping function can be employed to predict future data. Over the past two decades, a diverse array of supervised learning algorithms has been developed and widely adopted to enhance smart PG. Figure 6, provides a compilation of common supervised learning algorithms in the context of smart PG. Artificial neural networks (ANNs), designed to mimic biological nervous systems, have exerted a significant influence across various domains in recent years. ANNs, like many other machine learning techniques, do not require explicit programming but rely on algorithms to make predictions based on data [88,89].

Extreme Learning Machines (ELMs), employing a single hidden layer feedforward neural network, are a subtype of ANN algorithms. They have found applications in resolving smart power grid issues such as power system stability assessment and fault detection [90,91]. In this direction, the Back-Propagation Neural Network (BPNN) is a pivotal neural network learning technique that involves iteratively adjusting network weights until the error between the output and ground truth reaches a specified threshold. BPNN has gained extensive use in various neural network algorithms [92,93]. The Multilayer Perceptron, another feedforward neural network algorithm, is commonly employed. Moreover, the Probabilistic Neural Network (PNN) is a well-developed feedforward neural network model, that utilizes parent probability distribution functions of each class to estimate class probabilities for input data [94,95]. The k-Nearest Neighbors (KNN) algorithm, known for its rapid training capabilities, is also utilized in smart PG systems for both classification and regression tasks [96,97].

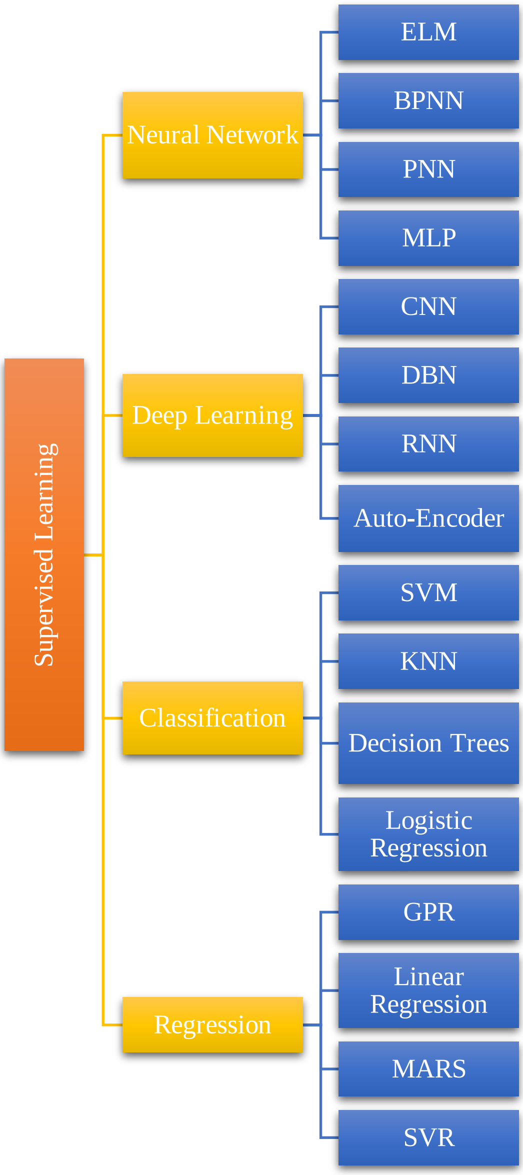

Figure 6. Supervised learning techniques in the smart PG.

C. *Unsupervised learning*

Supervised learning algorithms have demonstrated significant performance gains over decades of development. However, their effectiveness hinges on the availability of ground truth or prior knowledge of the patterns to seek, a circumstance not always guaranteed in real-world scenarios. This underscores the utility of unsupervised learning, which can uncover potential insights and hidden patterns within unlabelled data. Figure 7, presents a compilation of prevalent unsupervised learning algorithms. Unsupervised neural networks, such as the restricted Boltzmann machine, auto-encoder, and variational auto-encoder, find applications in tasks like anomaly detection, stability assessment, and load forecasting [98,99]. Clustering, an unsupervised task that involves grouping data points or populations based on similarity, employs methods like K-means, fuzzy c-means, and hierarchical clustering.

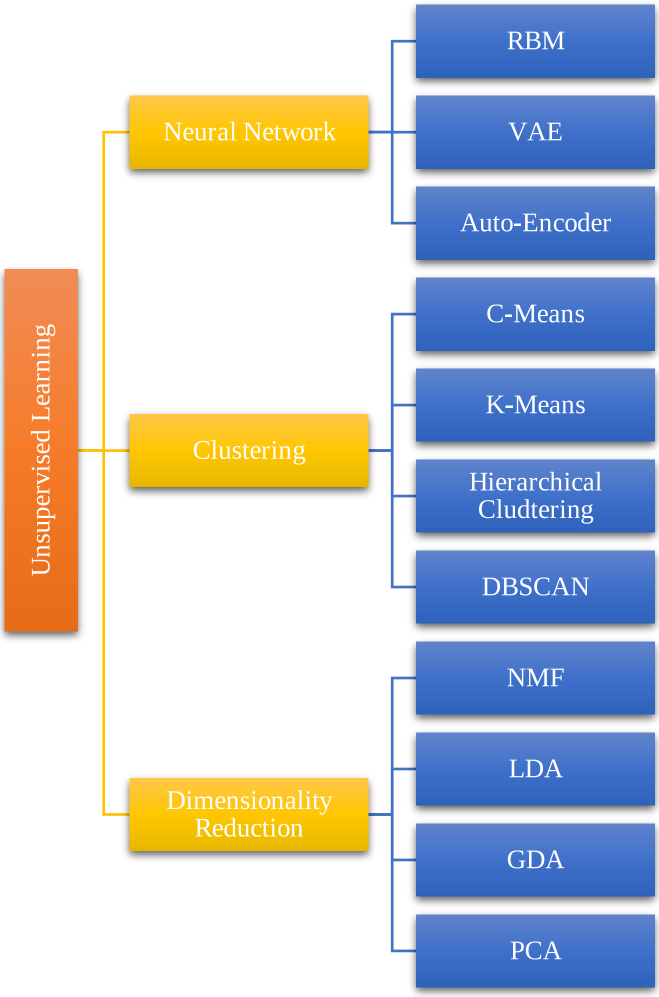

Figure 7. Unsupervised learning techniques diagram.

D. *Reinforcement Learning*

Reinforcement Learning (RL) has gained increasing popularity as an algorithmic approach for addressing challenges in smart PG integrated with the MESS applications. RL comprises fundamental components including an agent, environment, reward system, and actions. Its primary objective is to maximize cumulative rewards through a continuous process of receiving feedback, encompassing both rewards and penalties, for each action taken [100,101]. Figure 8, provides an overview of commonly employed RL algorithms. RL excels in scenarios where knowledge of the environment is limited, and feedback on decision quality is constrained, allowing it to adapt to unforeseen circumstances. Q-learning and SARSA (state–action–reward–state–action) find utility in tasks such as attack detection and energy management. Deep Reinforcement Learning (DRL), an algorithm that merges the perceptual capabilities of Deep Learning (DL) with the decision-making process of RL, has demonstrated remarkable success [102-104].

E. *Ensemble methods*

Ensemble methods, in the context of smart PG integrated with the MESS applications, amalgamate outcomes from multiple learning algorithms or diverse initial datasets to enhance overall performance. One such method, known as Bootstrap Aggregating or "bagging," assigns equal weight to each model in the ensemble and trains them using randomly selected subsets of data. A notable bagging model is the Random Forest, which effectively combines random decision trees with a high-performance classification algorithm. It finds application in tasks like load forecasting, anomaly detection [61,62], and stability assessment [105-108]. Another ensemble technique is "Boosting," which entails constructing a new model aimed at rectifying misclassifications made by the previous model. Boosting demonstrates promising outcomes in addressing smart PG challenges. Additionally, "Stacking" an ensemble learning approach that integrates predictions from various classification or regression algorithms, has seen substantial development for tasks like load forecasting, anomaly detection, and cyberattack detection within the smart PG domain.

4. Technical Challenges of Artificial Intelligence in Smart PGs

Traditional power systems, characterized by their intricate nature, rely primarily on physical modeling and numerical computations for analysis and control. The emergence of smart PGs integrated with the MESS, marked by a substantial integration of environmentally sustainable renewable energy sources and Microgrids, has initiated a shift from conventional PGs to more intricate smart PGs integrated with the MESS. This transition has brought to the forefront a multitude of uncertainties and complexities within the environment. Compounding these challenges is the utilization of aging infrastructure within the existing power system, further intensifying uncertainties in modern smart PG systems.

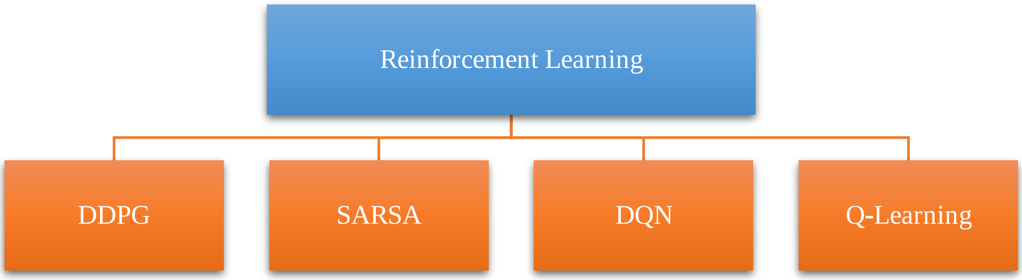

Figure 8. An overview of commonly employed RL algorithms.

As smart PGs integrated with the MESS closely intertwine with communication networks, they encounter the formidable task of managing vast quantities of data characterized by high variability. This continues to be a noteworthy challenge in the realm of smart PG integrated with the MESS. Furthermore, researchers are actively engaged in enhancing the robustness, adaptability, and real-time processing capabilities of AI algorithms. Despite the introduction of numerous data-driven methodologies aimed at addressing smart PG integrated with the MESS issues, several substantial challenges persist. These encompass but are not limited to the following:

- **Integration of Renewable Energy:** Smart PGs are distinguished by their extensive incorporation of renewable energy sources. However, this feature introduces a set of notable challenges due to the inherent variability and unpredictability associated with renewable energy. This unpredictability results in frequent and abrupt fluctuations in power output.
- **Ensuring Data Security and Privacy:** With the widespread deployment of diverse devices and bidirectional communication within smart PG integrated with the MESS, they become more susceptible to cyberattacks when compared to traditional power systems. As highlighted in the preceding section, numerous innovative security techniques have been developed to swiftly identify cyber risks, and mitigate issues such as false data injection, data theft, and electricity theft. Nevertheless, the network protocols, operating systems, and physical equipment employed in the current smart PG integrated with the MESS continue to expose the system to a wide array of potential attacks. Furthermore, the existing AI-based solutions for enhancing smart PG cybersecurity often involve trade-offs between security and performance.
- **Efficient Storage and Rapid Analysis of Big Data:** Another substantial challenge pertains to enhancing the efficiency of storing and retrieving the vast volumes of data generated by smart PG integrated with the MESS for AI applications. This challenge necessitates robust solutions for managing big data to ensure its seamless utilization in various applications.

- **Interpreting AI Algorithms:** In general, AI algorithms often suffer from the challenge of being perceived as black boxes, making them less interpretable and explainable. This issue represents a significant hurdle that AI algorithms currently encounter.
- **Constraints of AI Algorithms:** The integration of AI technologies significantly impacts the implementation of AI within smart PG integrated with the MESS. Nevertheless, it is imperative to carefully assess the limitations inherent in each AI method before its application within the smart PG context.

5. Directions and Prospects of Artificial Intelligence in Smart PGs

The primary aim of smart PG integrated with the MESS is to realize a fully autonomous system characterized by responsiveness, adaptability, self-repair capabilities, complete automation, and cost-efficiency. The forthcoming directions and prospects for advancing smart PG systems are explored as follows:

- **Integration with Cloud Computing:** To achieve a fully self-learning smart PG system, the integration of AI with cloud computing will assume an increasingly pivotal role. This integration not only enhances security and robustness but also minimizes disruptions in smart PG systems.
- **Prediction of Consumer Behavior:** With the aid of fog computing and the advancement of 5G networks, the management of demand on the consumer side has emerged as a crucial task. Understanding patterns in consumer behavior and power consumption holds significant potential for enhancing demand response initiatives from the consumer's perspective.
- **Fog Computing:** Fog computing is centered on the local pre-processing of raw data, eliminating the need to transmit this data to a distant cloud. Offering on-demand computing resources, fog computing boasts several advantages, including energy efficiency, scalability, and flexibility. Some research endeavors have ventured into integrating fog computing into the smart PG, and its importance is set to grow in tandem with the escalating data volume within future smart PG infrastructures.
- **Transfer Learning:** The persistent challenge of limited labeled data remains a central hurdle in smart PG analysis. Transfer learning, however, offers a potential solution by alleviating the data requirements, prompting researchers to employ it in addressing the issue of data scarcity. In recent times, there has been a growing focus on deep transfer learning applications [163], which hold substantial promise for a wide array of applications within smart PG.

6. Conclusion

In the ongoing transformation from conventional electric grid systems to advanced smart PG systems, the limitations of traditional power system methods in processing and managing the substantial data volumes inherent to smart grids have become evident. Consequently, there is a growing development and implementation of AI techniques across various applications within the smart power grid integrated with MESS, yielding promising outcomes. This article conducts a comprehensive survey, exploring recent applications of AI techniques in four critical domains: load forecasting, power grid stability assessment, fault detection, and security issues, which have not received comprehensive coverage in previous studies. Moreover, it addresses the present challenges, opportunities, and the future potential of AI techniques in realizing the full capabilities of a genuinely smart PG. Furthermore, the synergy between MESS and artificial intelligence (AI) techniques augments the potential of smart PGs to address contemporary challenges. This article illuminates the burgeoning role of AI, PG stability assessment, fault detection, and security enhancement within smart PGs and power systems. While acknowledging the complexities and forthcoming research challenges, it underscores that AI holds the key to fortifying the reliability and resilience of smart PG systems. In essence, the future of energy lies in the fusion of innovative technologies like MESS and AI, driving the transition towards sustainable, intelligent, and efficient smart PGs that are capable of meeting the evolving demands of our rapidly changing world.

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data curation, all authors; writing—original draft preparation, M.K.; writing—review and editing, all authors; visualization, all authors; supervision, all authors; project administration, M.K. All authors have read and agreed to the published version of the manuscript.

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