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Comprehensive Review of Artificial Intelligence for Shaping Renewable Energy Power Systems

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ABSTRACT

Renewable Energy Sources (RESs) are widely penetrating power systems, due to their environmental compatibility and shortage reserve of the fossil fuels. This mandates the application of intelligent, innovative and smart techniques for forecasting, controlling and managing of RESs. However, RESs suffer from uncertainty, weather and operating condition dependence, which considers as a major challenge of the conventional controlling strategy.

Artificial Intelligence (AI) enjoys the advantage of adapting the control and operating routines according to the system status, which is attributed to the numerous training scenarios. AI in the areas of RESs could improve their reliability, security and sustainability. Moreover, AI could boost the operation of different energy storage systems, which are considered integral part for different RESs system. This article comprehensively analyzes several literatures regarding AI for RESs. Moreover, comprehensive comparisons between conventional controlling and driving systems of AI in fields of RESs are given in the article. The article moreover addresses the storage system for RESs and the impact of application of AI in improving the energy management of such systems. The article acts as simple and reliable tools for researchers and engineers in the area of AI for RES.

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مراجعة معمقة حول الذكاء الاصطناعي لصياغة منظومات الطاقة المتجددة

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ملخص: دخلت مصادر الطاقة المتجددة في أنظمة الطاقة على نطاق واسع، نظرًا لتوافقها البيئي ونقص احتياطي الوقود الأحفوري. و يفرض هذا التحول تطبيق تقنيات ذكية ومبتكرة للتنبؤ بمصادر الطاقة المتجددة والتحكم فيها وإدارتها. ومع ذلك، تعاني مصادر الطاقة المتجددة من عدم الثبات وتغيرها تبعا لحالة الطقس وظروف التشغيل، وهو ما يعتبر تحديًا رئيسيًا لاستراتيجيات التحكم التقليدية. بينما يتمتع الذكاء الاصطناعي بميزة تكييف روتين التحكم والتشغيل وفقًا لحالة النظام، وهو ما يُعزى إلى السيناريوهات المفترضة العديدة التي تم تدريب النظم عليها. كما يمكن للذكاء الاصطناعي في مجالات مصادر الطاقة المتجددة تحسين موثوقيتها وأمنها واستدامتها. علاوة على ذلك، يمكن للذكاء الاصطناعي تعزيز تشغيل أنظمة تخزين الطاقة المختلفة، والتي تعتبر جزءًا لا يتجزأ من أنظمة مصادر الطاقة المتجددة المختلفة. يحلل هذا المقال بشكل شامل العديد من الأدبيات المتعلقة بإستخدام الذكاء الاصطناعي مع مصادر الطاقة المتجددة. علاوة على ذلك، يتم تقديم مقارنات شاملة بين أنظمة التحكم التقليدية والذكاء الاصطناعي في مجالات مصادر الطاقة المتجددة. كما يتناول المقال نظم تخزين مصادر الطاقة المتجددة وتأثير تطبيق الذكاء الاصطناعي في تحسين إدارة الطاقة لهذه الأنظمة. تعتبر المقالة بمثابة مراجعة بسيطة وموثوقة للباحثين والمهندسين في مجال الذكاء الاصطناعي لمصادر الطاقة المتجددة.

الكلمات المفتاحية – مصادر الطاقة المتجددة، الذكاء الإصطناعي، أنظمة الطاقة، الإستدامة.

1. INTRODUCTION

RESs are a measure towards lowering Green House Gases (GHG) emissions and counteracting climate change impacts [1]. Which lead the installment capacity of renewable energy across the globe to increase by 50 % in 2023 to become 3,372 GW of solar, wind, hydropower, geothermal, marine and biogas energy by the end of the year 2023. The market is expected to grow at more than 4.22% in the future. Some countries leading the way in RES production: China is in the first place in terms of cumulative installed PV power with760 GW, the USA is second with 265 GW. While in Africa the production mainly consists of hydropower, photovoltaic solar plants, and biomass energy [2]. The installed capacity in Africa amounted to approximately 221 GW. The irregularity and instability of these energy sources, however, creates problems for the control of the grid and of energy delivery [3]. To overcome these challenges AI has been incorporated as an effective tool for enhancing energy production, storage and supply.

Currently, techniques such as Machine Learning (ML), deep learning and reinforcement learning have now been extended to enhance the RESs performance, reliability and flexibility[4]. Based on the AI capabilities to process petabytes of data and make real-time decision-making, improvement of the integration of RESs into energy grids, covering the problems of intermittent nature and enhancing the grid stability[5].

The management and control of energy systems have been done using conventional approaches which include Proportional Integral Derivative (PID) and Model Predictive Control (MPC)[6]. Although such methods work well in relatively slow changes, for example, in climatic changes and power load changes, they do not work very well in uncertain changes. This is so because conventional techniques are unable to respond on the fly thus, energy is wasted, the grid is altered in a negative way and renewable resources when available cannot be utilized fully[5].

These are the recent development of the AI as a problem solver in the energy sector, where conventional techniques cannot come near to. Intelligent systems employ sensor data, meteorological data or/and historical data of the plant to forecast and manage the generation and storage of energy for peak demand [7]. This means that through using machine learning algorithms over such datasets, AI systems will be applied to determining the dynamic change of energy flows while at the same time predicting the demand and supply levels of the RESs[8]. For instance, AI has applied in improving the solar and wind energy systems through better forecasting and real-time patterns correcting the systems' operations. It is also being applied to the ESSs where it helps in managing the charge as well as the discharge cycles to minimize wastage and enhance the systems performance[7].

This review article presents a full accounting of the factors that relate to the use of AI to enhance renewable energy systems. The article compares the conventional control methods and AI-based control methods. The article explains different renewable energy systems. Also, the article discusses the energy storage systems including control and management. The article is claiming to have the following contributions:

- A review of benefits and drawbacks of conventional control technics in RES and ESS.
- A assessment of the roles that AI plays in enhancing the productivity, durability and cost of RES. Analysis of different ESS and the role of AI in improving the functionality and performance of these systems.

The review is organized into the following sections: Section 2: Methodology, including - RES for electricity production: discussing the ways in which artificial intelligence improves the solar and wind systems alongside a comparison with conventional methods.

- Energy Storage Systems for RESs: gives particular attention to the application of AI in energy storage management where it shown how AI optimizes charge/discharge cycle and impacts energy efficiency. Section 3: Conclusions and future work: In this part, several findings are discussed and outline AI prospects in the renewable energy field and further research limitations and drawbacks.

2. METHODOLOGY

The integration of artificial intelligence (AI) in renewable energy (RE) systems has significantly advanced the management and optimization of energy generation, storage, and distribution. Various AI techniques, including machine learning algorithms, have been employed to enhance the efficiency and reliability of RE systems. This response will explore the AI techniques utilized in RE, the governing equations of renewable and storage systems, and the eco-economic analysis associated with these technologies.

Techniques such as Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Genetic Algorithms (GA) are widely used for forecasting and optimizing energy production and consumption[9][10]. Particle Swarm Optimization (PSO) and Convolutional Neural Networks (CNNs) are applied to improve grid management and energy storage systems[9][11].

AI facilitates the integration of multimodal data for enhanced forecasting and performance monitoring in variable renewable energy systems (VRES)[10].

The governing equations typically involve the balance of energy input (solar, wind) and output, considering factors like efficiency and capacity factors. The equations governing storage systems, such as batteries, include charge-discharge cycles, state of charge (SoC), and energy loss mechanisms, which are critical for optimizing storage solutions[12][13].

Evaluating the economic viability of integrating AI in RE systems involves analyzing initial investments against long-term savings and environmental benefits[12][14]. Effective governance and incentives for renewable energy adoption, including subsidies and technological innovation, are essential for maximizing the economic benefits of AI-enhanced systems[12]. While the application of AI in renewable energy systems presents numerous advantages, challenges such as data quality, integration complexity, and the need for regulatory frameworks remain significant hurdles that require ongoing research and development.

2.1. Renewable energy sources for electricity production

RESs vary according to the geographical location, hence some countries have plenty of the different types of RES, while the other are usually limited to one or two types at the most. Figure 1 show a predicted renewable electricity production capacity from the International Energy Agency (IEA). The wind and solar energies represent the most widespread types of RES. The real power (P_{PV}) of the PV panel under real operation and climatic conditions in Eq.1.

$$P_{PV} = P_{STC}\left[1+\beta_p\left(T_{cell}-T_{STC}\right)\right]\frac{H_t}{H_{STC}} \qquad (1)$$

Where: T_{STC} and T_{cell} are the celll's surface temperature at Standard Test Condition, β_p the power temperature coefficient. The challenge that researchers will face is to find an empirical equation to determine the cell surface temperature T_{cell} For example [15].

As for the wind turbines the climate changes affects the wind speed which make generation difficult in low speed and shut down is necessary in high speed to avoid destruction Eq.2.

$$E_W = \begin{cases} P_{rat}\left(\dfrac{V_{Z,t}-V_{cut-in}}{V_{rat}-V_{cut-in}}\right) & V_{cut-in} < V_{Z,t} < V_{cut-off} \\ 0 & V_{Z,t} \leq V_{cut-in}\, OR\, V_{Z,t} \geq V_{cut-off} \end{cases} \qquad (2)$$

Where: P_{rat} is the rated power of the wind turbine at rated wind speed V_{rat}, V_{cut-in} and $V_{cut-off}$ are the cut-in and cut-off wind speeds, and $V_{Z,t}$ is the wind speed at the wind turbine hub height (h_Z) and it is calculated from: $V_{Z,t} = V_{,t}\left(\dfrac{h_Z}{h}\right)^{\propto}$;

Where, $V_{0,t}$ is the wind speed at a certain elevation (h_0) and α is the wind shear coefficient [16]. Future predictions suggest that the wind speed may rise up to 45% under certain climate scenarios during winter thus improving the potential of generating electricity based on high-resolution climate change [1].

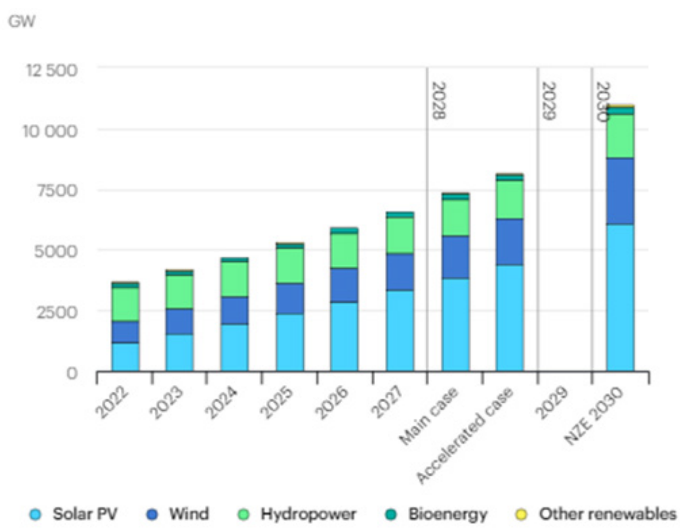

Figure 1: renewable electricity capacity in the main and accelerated cases and Net Zero Scenario, 2021-2030 (SOURCE: IEA).

Future of wind power is expected to increase with expectations of it increasing from 4.7 Million Tons of Oil Equivalent in 2001 to 688 Mtoe by 2040 [3]. the solar photovoltaic systems are expected to get rapid expansion based on scenarios for Future perspectives for wind and solar electricity production; the rated capacity is envisaged to rise from 0.2 in 2001 and will reach 784 Mtoe in 2040 [3]. certain regions may experience improved solar irradiance during winter due to specific atmospheric conditions, Such dependencies may result in 45% raise in generation which can affect the energy market directly [1].

The application of traditional methods of controls in renewable energy systems has direct impacts on the effectiveness of power production. These methods, however, can be refined by a number of advanced approaches that greatly enhances both effectiveness as well as dependability while improving performance. These include Proportional Integral Derivative control, Model Predictive Control and Sliding Mode Control which offer sound approaches for dealing with the nature of variability characteristic of renewable sources. Proactive and supervisory controls are foundational for the effective application of renewable energy systems' control strategies. It assists in the coordination of the different energy sources in the system hence enhancing the performance of the system [17]. An analysis of recent studies reveals that an innovative technique for predictive current control is better than conventional methods in decreasing the present current harmonics as well as maintaining improved power quality for the integrated systems like wind and solar energy power system [5].

It has been evidenced that fractional-order control concepts are more effective in modeling and controlling the renewable energy systems in contrast to integer order methods resulting in lower average errors in performance [6].Some of the methods such as MPC is effective in providing real-time response in energy demands to attain the best efficiency of the power from renewable sources[18] [8]. And variable control measures can be implemented so that energy production guessed fares with the demand level to reduce wastage [17] Figure 2: show the Announced Pledges Scenario for wind and PV share in power generation. Reliability engineering principles also assist in maintaining a constant energy production since the focus is now on integrating renewable energy sources hence the uncertainties that accompanies this kind of energy sources [19]. Control methods such as Sliding Mode Control are even specific to the operational non-linear systems to guarantee a stable performance under different parameter alterations [8].

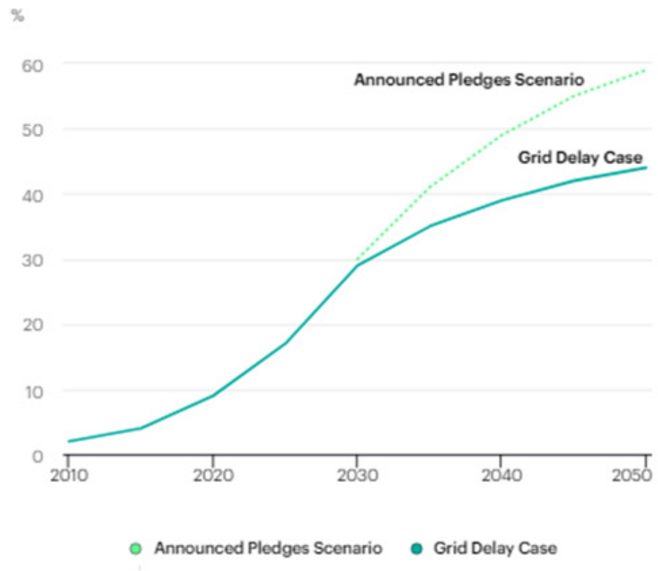

Figure 2: Share of solar PV and wind in power generation worldwide in the Grid Delay Case and the Announced Pledges Scenario, 2010-2050 (SOURCE: IEA).

Although there are significant advantages of applying the classic control, some issues still persist regarding the connection of such systems to the current power networks including scalability and the need for better monitoring devices [20]. Solving these problems is critical to achieve the full potential of renewable energy systems because the use of rigorous control theory tools sometimes hinders the ability of renewable energy systems to fine-tune the system to conditions that are constantly changing. These are some of the issues that need to be overcome through integrating more advanced approaches, like the reinforcement learning, to boost efficiency [21].

2.2. AI and conventional techniques in control of RESs

Therefore, it is necessary to know the advantages and disadvantages of each strategy, especially in the context of handling real-time data and dynamic environment. The control strategies applied in renewable energy systems have a very vast difference between the conventional technologies and AI technologies.

Traditional ways of controlling systems like the PID controllers barely succeed in controlling the nonlinear behavior of renewable systems thus limiting their performance in large-scale systems. On the other hand, there are control methods like adaptive neuro-fuzzy inference system (ANFIS) and predictive algorithms, which offer improved response with higher system performance due to their ability to adapt the change in conditions [22].

2.2.1. Implementing AI with Conventional Techniques in RES

Ref. [5]: Implemented a control approach based upon MPC approach to improve the integration of renewable energy sources. The model was validated for the hybrid wind and standalone solar power systems. MPC-based systems gain in energy capture efficiency compared to the conventional control methodologies. This approach helped in a more accurate prediction leading to a better balance in the energy grid in the process simplifying the grid stability.

Ref. [6]: discussed the topology of fractional-order control methods for power systems with an emphasis on PID control with implemented renewable power sources and energy storage systems, As for these systems, simulated in MATLAB to analyze for stability of the control as well as the control performance. Systems with the fractional-order PID controllers outperformed the traditional methods of handling fluctuating renewable energy and energy storage systems. It was also found that the proposed method proved to be efficient in minimizing overshooting and achieving faster system response, especially for the proposed hybrid renewable systems.

In [8] an analysis of some of the control methods such as Sliding Mode Control SMC and MPC in energy systems is presented, and checked the efficiency of these techniques in the perspective of possessing ability of real-time adaption and changes. MPC was identified as being most useful in controlling energy and make actions to minimize losses with SMC also useful for applying good results under conditions of high variance. Also it was established that both of the mentioned methods possessed the capability of decreasing operational costs of renewable energy systems.

Ref. [18] presents an overview of Multiport Converters (MPCs) for interfacing Renewable Energy Sources, offers a new classification of these converters according to the applications, and presents common control strategies and limitations for such systems.

The authors in [19] summarized the actual reliability engineering fundamentals used for the renewable energy systems. Mode of failure most common in wind and solar installations were determined through Reliability Centered Maintenance (RCM) and Fault Tree Analysis (FTA). The implementation of RCM brought positive changes in reliability of renewable energy systems, whereby system availability increased therefore, confirmed the most severe problems of inverter and storage unit, thus indicating concerns that the improvement of maintenance strategies would certainly improve system durability.

Ref. [20]: Analyzes some of the metaheuristic algorithms that were used for optimizing photovoltaic

(PV) panel models include, Particle Swarm Optimization (PSO), and Genetic Algorithms (GA). Performance assessment was done by comparing the results to the ground truth by using Mean Squared Error (MSE) and the energy conversion efficiency as the measurement parameters. PSO had better accuracy than the other algorithms with PV model prediction while GA offered improved solution taking into account high variability. Both approaches ensured increased conversion of the solar energy and ensured that the systems were more reliable.

the DRL categories are discussed in [21]. [11] surveyed the DRL approaches and explained the DRL approaches to renewable energy control systems in some case studies whereby power dispatch policies in solar or wind farms was enhanced by DRL models; DRL applied to the management of power systems cut the instability level and improved the real power demand, thus boosting the use of renewable energy. and the technique was effective in managing one of the biggest sources of uncertainty in the model which is the availability of renewable energy.

2.3. Main differences in control strategies

AI methods allow environmental dependencies along with grid stability and power management and classic methods generally involve constant values [22]. Fuzzy logic and sliding mode control improved the power performance coefficient in small-scale wind turbines, as compared to a limited dynamic response of classical methods [23].

Consequently, AI approaches handle the challenges of microgrid implementation, including energy and storage management, which could not be addressed using conventional methods [24].

Although AI control strategies show better flexibility and optimality, classic methods do not lose their efficiency in cases with limited computational capabilities. The selection between these methods depends on the criteria of the renewable energy system that is being implemented.

2.3.1. Different approaches applied for power systems control

Ref. [22]: Applied Adaptive Neuro-Fuzzy Inference System ANFIS for advanced controlling of grid connected PV-wind hybrid energy system. For this purpose, historical energy production data were used for training ANFIS which aims to forecast energy production and enhance system control. The proposed ANFIS-controlled hybrid system achieves energy efficiency and load balancing as compared to the conventional control methods. The given strategy was helpful in minimizing wastage of energy and increasing system's capacity to handle supply volatility.

In [23] the control strategies for Horizontal Axis Wind Turbines (HAWT) are reviewed, which includes pitch control, torque control and individual blade control. The assessment was made according to literature and case studies to consider the efficiency, reliability, and power output. Pitch control was the most viable way of maximizing power when applied to the overall configuration of the wind turbine system information while Individual blade control on the other hand was most useful in managing the loads placed on turbines by varying wind conditions to enhance their durability and reliability.

Ref. [24] Searched for control strategy for microgrids for review and categorization into centralized control, decentralized control and hierarchical control. Employed different microgrid configurations to evaluate the flexibility of such methods in response to variations in renewable energy feed-in. Out of the control strategies studied, hierarchical control approaches were found to have excellent performance to manage the load and generation responsibilities in real-time while maintaining stability. Decentralized control had the potential for be used in remote or off-grid microgrids but failed in high demand situations.

Ref. [25] reviewed on the best control strategies such as Linear and Nonlinear control, Predictive control and prefixed control algorithms such as Genetic Algorithms (GA). These methods were applied on number of cases that include wind and solar power systems. Predictive control bestowed

the highest accuracy when it came to the prediction of energy production and consumption aspects that improved system's reliability. However, the compound nature of nonlinear systems and the high computation required as a result was a limiting factor for large scale application.
Ref. [26] looked into the application of Machine Learning (ML) and IoT in solar energy system management, pay attention to; predictive maintenance and system optimization. ML such as the neural network Implemented and experimented in fault detecting, and energy forecasting. The ML-IoT framework enhanced the prediction of solar power by an increased accuracy by reducing system downtime. Thanks to the IoT sensors used for monitoring the various systems, as well as the ML algorithms implemented to increase the general effectiveness of the system, there was nominal monitoring on real-time.
Ref. [27] discussed the current development in advanced control strategies for Building and District energy storage systems. This is specific on techniques such as Model Predictive Control (MPC) and rule-based control in the efficient use of energy storage and the reduction in the peak load demand. MPC was the most effective, as it lead to the decrease of the maximum energy load by 25% and increase of the energy utilization. While rule-based control was easier to apply in terms of management and regulation, it provided low performances in conditions of high variability of energy amounts.
Ref. [28] focused on the reinforcement learning and deep learning for optimization of renewable energy systems. these techniques used for enhancing efficiency of energy storage systems and wind and solar power systems. Analysis showed that reinforcement learning algorithms delivered better results in optimizing energy storage and dispatch issues resulting to a gain of fifteen percent in the system efficiency. Various deep learning methods allowed for increasing the accuracy of energy demand forecast.
Ref. [29] employed RL techniques for a joint design and control for the energy system. Limited testing RL in a scenario where there are renewable energy systems, and the generation as well as distribution of energy is to be optimized simultaneously. The optimization based on RL minimized energy losses by 10% as well as enhanced stability in the system. The authors concluded that co-optimization approach helped in finding a more optimal solution with regard to the integration of higher levels of RES but high computational expenses where reported as a downside making the approach rather unsuitable for a real time operation.
Ref. [30] proposes a new approach of integrating PID with MPC to control of Energy Storage Modular Multilevel Converters (ES-SIMMC), this has been tested on a simulated energy storage system. The integration of the new control technique enhanced the voltage regulation while reducing the power losses. PID and MPC showed a favorable dynamic response and less system wear where there were variations in power demand.
Ref. [31] studied the effects of sample size in the aspect of storage control of renewable energy systems. Described the amount of data required for training efficient control algorithms for energy storage systems employing statistical methods and simulation Shown that for efficient storage control it may be enough to control fewer data points than was thought of before. Advanced control algorithms enhanced system efficiency with less training data requirements than before thus being more implementable in real-use applications.

2.4. ML algorithms with classical control methods

The effectiveness of renewable energy systems can be improved by combining the ML algorithms with classical control approaches. This integration makes it possible to enhance the aspects of predictive maintenance, energy yield efficiency, and control flexibility, and this makes for more dependable and efficient energy solutions [25].There is a possibility of applying artificial intelligence and machine learning algorithms with a new generation data-analysis tool: Artificial Neural Networks (ANN) that can predict maintenance requirements based on historical and real-time data with relatively high accuracy [26].This predictive capability cuts down on power losses and reinvestment expenses guaranteeing steady functioning of renewable systems [27]. Genetic Algorithms (GA) and Reinforcement Learning (RL) have potential of enhancing the energy output by 20% in hybrid system and by 15% in solar PV system [28]. Such optimizations not only increase productivity but also result in massive savings in costs and minimization of the environmental footprint [28].

The combination of ML with classical controllers like PID leads to the dynamic adjustment of the system based on environmental conditions [26].This flexibility is paramount for handling the variability that characterizes renewable electricity sources will enhance power grid reliability [29].

The application of ML in conjunction with the traditional control techniques has a number of benefits but also concerns such as data integrity and model comprehensibility. The mitigation of these things is crucial in achieving the full potential of renewable energy systems.

Despite its popularity, the traditional PI control has some drawbacks, including creating potentially higher circulating current in some energy storage systems. A new study comparing a conventional system with an improved one has indicated that the incorporation of model predictive control (MPC) is a beneficial improvement, as it shortens the execution time. As to PI methods [30]. in [31] The article cautions that a good energy storage control is dependent on the quality and quantity of the demand data. Lack of data may result in less accurate control and less effective performance of the controller. Sample complexity theory underlines the conflict of interest between data sample size and controlling efficiency, which stresses the importance of robust data sampling methods.

2.5. Energy Storage Systems for RESs

The use of renewable energy source, particularly solar and wind power has some limitation due to their fluctuating nature. ESS is important to increase the efficiency and the level of reliability of these renewable resources. Through incorporating ESS, all the advantages of the use of renewable energy can be regulated to give a sustainable energy environment [32]. Generally speaking, ESS can store energy that is produced in the periods of high generation and release it in the periods of low generation, thus guaranteeing the population in constant power supplies [33].

Figure 3 shows Global installed energy storage capacity by scenario, 2023 and 2030.

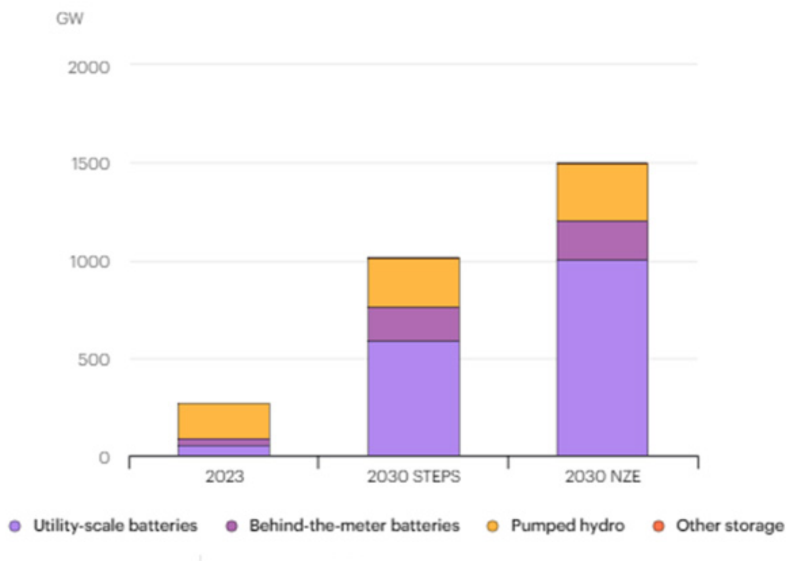

Figure 3: Global installed energy storage capacity by scenario, 2023 and 2030 (SOURCE: IEA).

Some of the critical factors which affect energy storage capabilities of renewable energy systems bear the imprint of the timeless control approaches.
These methods improve the control of energy storage systems (ESS), improving both efficiency and durability of the controlled ESS as well as tackling with the stochasticity of renewable sources [34]. while Conventional control methods have far reaching effects on energy storage capacity of the system affecting the efficiency and effectiveness of energy control in power systems. Integrating higher control techniques can improve the use of energy storage systems and the performance of the system in general [35]. Also, the deterministic control methods can be improved by integrating real-time data analytics alongside performance-predictive algorithms so as to develop more agile energy management solutions that cater with the demand and supply volatility [7].
This capability addresses the issue of fluctuating renewables which makes the grid integration and stability better [36]. Advanced energy storage technologies, which increase charge/ discharge rate and cycle.life, making renewable energy systems more economically viable [37].The development of cost-effective storage solutions is essential for maximizing the output from renewable sources, thereby reducing reliance on fossil fuels [38].
Through enhancing the utilization of renewable power ESS helps to lessen the emission of greenhouse gases to the atmosphere hence encouraging the preservation of the environment [33][38].
Ref. [32]: Examined specific renewable ESS including batteries, flywheels, and hydro pumping. The examination included characteristics of analyzed performance metrics such as energy density, efficiency rates, and ESS costs for different types of ESSs. Out of all the battery storage technologies available, lithium-ion battery storage was regarded as the most suitable because of factors such as energy density and decreasing costs. Flywheels were seen ideal for short-term storage while hydro pumping remained to be the perfect solution for long-term and utility scale storage.
Ref. [33]: Looked at the applications of energy storage in renewable energy systems, the utility-scale as well as the residential-scale. The efforts mostly directed at battery systems, thermo-storage materials, and mechanical storage elements, such as flywheels and pumped hydro storages. Battery storage was identified to be the most flexible and suitable for implementation in the both areas of grid and residential. Hence, pumped hydro was considered efficient for long term storage and for large scale demand and flywheels for the short term applications.
Ref. [35]: Considered different aspects of the present day ESS which includes batteries, flywheels, super capacitors and hybrid ESS for integration of renewable energy sources into the grid. The research identified that lithium-ion batteries are the most common because of power density and efficiency, and, moreover, systems including several types of storage provided maximum results. It also pointed out critical issues like the cost of the material and sustainability of material, this made the authors call for further research on recycling technologies.
Ref. [36]: Explored a PV system for connection to the electrical grid with battery storage. The simulation tools were used to investigate the flow of energy both from the solar panel to the battery and the grid and from the battery to the grid under various conditions. The system helped in increasing grid stability by storing the excess solar power then provided power during outages. The simulation also revealed an improvement to the system efficiency and was cheaper in terms of energy cost.
Ref. [38]: Summarized and evaluated energy storage technologies to integrate renewable energies such as batteries, super capacitors and flywheel, Discussed range of application of each technology in the grid stabilization, frequency regulation, and load balancing. Among all the systems, lithium-ion batteries were determined most applicable for grid-level storage through having both high energy density and cycle life. Flywheels offered the most favorable response for frequency

regulation since they offered fast response to signals as compared to other technologies such as the super capacitors whose primary role was to provide short-term storage for balancing the grid.

2.6. Control Techniques Impact on Energy Storage Capacity

Optimization of energy storage control strategies derived from voltage sensitivity analysis can enhance the PV hosting capacity of LV grids without significant communication networks [39]. Optimal control can reduce the amount of energy to be stored for overvoltage prevention thus maximizing the use of available storage systems [39]. The use of control methods such as constant current constant voltage can safeguard batteries from degradation thus improving their useful life and cutting the costs of replacing batteries [40]. Figure 4: Global installed grid-scale battery storage capacity in the Net Zero Scenario, 2015-2030.

Sophisticated predictive control methods could mitigate the variability of power output in most renewable energy systems, hence placing them in a better position to balance their energy interchange with the utility more effectively [41]. Table 4: show some work consider the control role for effective ESS.

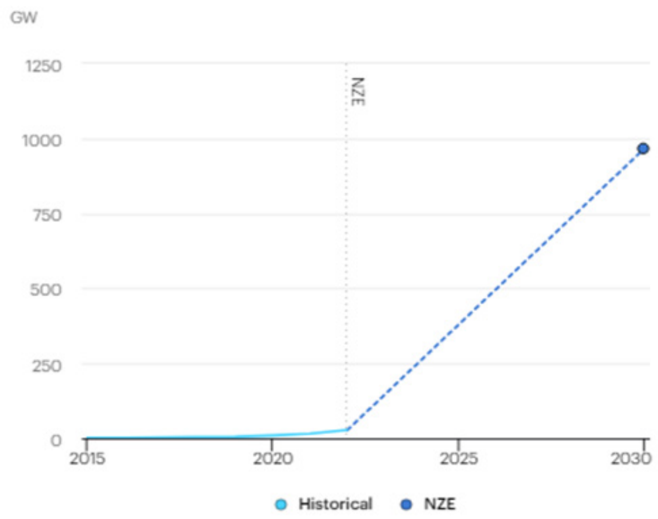

Figure 4: Global installed grid-scale battery storage capacity in the Net Zero Scenario, 2015-2030 (SOURCE: IEA)

2.6.1. Control role on effective ESS

Ref. [34] came up with control strategies for energy storage systems ESS in microgrids incorporating renewable energy sources. For real-time operation of ESS, it incorporated the model-based predictive control (MPC) technique besides the dynamic programming. The control strategies increased the efficiency by controlling the power exchanges between RES and ESS, and by decreasing dependency on the grid. MPC improved real-time performance and optimized the microgrid more than a baseline, including under conditions of peak load.

Ref. [7] presents an integrated Model Predictive Control (MPC) structure for grid interfaced energy storage systems. The method was intended to facilitate the management of many different ESS units to cover optimal energy circulation. The synchronized MPC approach resulted to decrease of operational expenses and enhance the stability of the grid by addressing issues of supply and demand especially during the peak times. The system also had better approaches for incorporating the variable renewable energy sources.

Ref. [40] discuss charging and discharging control approaches to battery for renewable energy systems. Concentrating on control techniques and approaches for battery performance including

fuzzy logic, neural networks and predictive control. Of all the possibilities to control the battery charge/ discharge cycles fuzzy logic and predictive control yield the best outcome as to the increase in battery life. Neural networks enhanced the accuracy of the forecast for energy, and taking advantage of this accuracy, the further development of the system improved efficiency.
Ref. [41] studies the applicability of the predictive control based on the neural network for the renewal hybrid system (HKT-PV) in order to minimize fluctuations in the output power level. The control strategy was implemented on simulation environments, to assess the feasibility on realistic scenarios.
Ref. [42] Reviewed market trends in the EV market and the charging infrastructure.
Also challenge assessment and recommendations on integration of EVs to the grid
With regards to the power fluctuation, the neural network approach yielded good results and made the power smoother. It also enhanced overall system efficiency and guarantee that energy delivery was constant, especially on times of fluctuating solar and wind generation.

2.7. Effect of Conventional Control on Energy Storage

Early work approaches used in designing the microgrids tend to amplify the frequency signals hence, these results in poor utilization of Battery Energy Storage Systems BESS. A new VC strategy called virtual inertia control with state of charge recovery reduces energy demands while holding state of charge (SOC) levels constant and synchronizing BESS utilization with the grid [43].
Traditional methods have a problem with varying power from renewable sources. Advanced predictive control technologies including neural networks has been found to have minimized energy variations, controlling battery SoC, and avoiding deep discharge that accelerate battery degradation [41].
In the low voltage grids particularly on long feeder sections, normal control strategies may not suffice to handle with overvoltage problems. The modern control methods utilizing voltage sensitivity analysis can considerably decrease the energy storage for overvoltage mitigation, thus augmenting the hosting capacity for photovoltaic systems [39].

2.8. AI roles In Energy Storage Systems

Machine learning and artificial intelligence working into the ESS to increase the efficiency and reliability and performance. Neural networks and optimization algorithms are also being used to improve the management and control of these systems. methods such as Particle Swarm Optimization (PSO) and Artificial Neural Networks (ANN) are employed for better and efficient thermal energy storage systems design and operation [44].
The predictive models for wind farms and molten salt storage performance as integrated systems are based on Artificial Intelligence, AI, and the data obtained with the utilization of the Multilayer Perceptron ANN approach with the average absolute percentage deviation [45].
Non-linear autoregressive networks with exogenous inputs NARX reveal the adequacy of monitoring the state of charge and outlet temperature in latent heat storage systems the detected dependence is characterized by high accuracy with R^2 above 0.99 [46]. Active Disturbance Rejection Control (ADRC) using ANN improves the dynamic performance of dual-active-bridge-based ESSs; the load voltage can be rapidly regulated in dynamic conditions [45].

2.8.1. Novel concepts in ESS control.

Ref. [43]: introduces an assessment of a novel concept named Virtual Inertia Control (VIC) strategy with SOC recovery strategy which is applied for enhancement of secondary frequency control with batteries on isolated grids. Thus, the operation of the VIC algorithm provides the synchronous generator inertia, stabilizing oscillations of frequency. SOC recovery as far as prolonged disturbances are concerned aims at preserving capacity on BESS thereby avoiding deep discharging. Under different load and renewable energy profiles, simulations were performed. VIC helped support better frequency stability in situations where the share of 'low inertia' was increased by keeping the frequency as close to nominal as possible during disturbance.

SOC recovery also helped in extending life of batteries through barring deep discharging incidences in most cases. This overall strategy helped in reduce stressing BESS and at the same time allowed the batteries to provide the optimal performance along with maintaining grid vitality.

Ref. [44] studied various applications of artificial intelligence (AI) in making prediction and control and optimization of thermal energy storage (TES) systems. Neural networks, machine learning and genetic algorithms were used for different tests for assessing their effects for controlling TES under different operations. According to this, the performance of the AI models was tested through simulations with reference to conventional control techniques. Based on machine learning, higher prediction accuracy of energy demand and better optimization of charge/discharge cycles were demonstrated. Some of the improvements achieved in this element include energy flow management which overall led to the cheapening of operations.

AI models also helped the TES system to optimize operational processes in real-time, and increase flexibility and scalability of the entire system.

Ref. [45] introduced a new Active disturbance rejection control ADRC strategy along with a new Artificial neural network ANN To control the energy flow in the proposed dual active bridge based energy storage system, ADRC is aimed towards system disturbances and dynamic load changes, on the other hand ANN refines the control precision by detecting behavior of the system. The system response to varying energy demand was tested through simulations and laboratory experiments. The combined ADRC-ANN control presented greater performance in terms of disturbance attenuation and system response time than the conventional controllers. Advantageous energy transfer efficiency, continuity of operations was mentioned with the facility exhibiting improved transition between different modes of operation. This proposed control strategy also minimized energy losses and enhance the dependability of the energy storage system.

Ref. [46] introduces a Non-linear Autoregressive Network with Exogenous Inputs (NARX) to analyze the dynamic behavior of latent heat thermal energy storage (LHTES) systems. The NARX model was tuned with historical operating data regarding the energy storage and energy release mechanisms under different load conditions. A comparison was made between NARX predictive models for system performance and those of other models. Thus, the NARX model provided more accurate predictions, as well as more efficient computations, compared with conventional predictive models. More accurate planning of such dynamic activities allowed for a better decision on charge and discharge cycles. This approach has helped in improving the aspects of LHTES systems, namely, energy consumption, energy loss and system reliability.

Ref. [47] discusses the differences between different grid-interactive building control algorithms including model-based and machine learning-based (ML). Algorithms that were used in this study were examined to assess their knowledge in the procedures of energy use in the grid connected building with concentration on real time demand for energy. MPC, RL and other ML approaches were evaluated with respect to their adaptability in optimizing the energy utilization according to the grid status. Compared to the other approaches, the learning-based methods especially Reinforcement Learning had higher performance in terms of flexibility which learned from the past experience and takes more energy-conscious decisions. According to the analysis made RL-based control strategies were more applicable in the dynamic scenarios like varying energy prices and integration of renewable energy sources. As a result of the study, it was found that the employment of ML approaches affords better energy saving than traditional model-

based techniques.
Ref. [48] studied the application of intelligent algorithms in the power control of battery storage systems in microgrids with dynamic pricing structure. Some of the optimization techniques employed in the optimizing of battery charging and discharging includes PSO as well as genetic algorithms under time varying real electricity prices. The algorithms ensured both the cost of energy as well as the reliability of the system was optimized. The AI-based control measures effectively managed battery dispatch resulting in low utilization costs especially during high price periods. This intelligent control system was capable to react to changes in prices of electricity, offering affordable concentrations of energy storage. Battery durability was also increased owning to optimization of charging/discharging routines, preventing deep discharge cycles.

2.9. Effects of using AI and conventional techniques in ESS

Self-learning algorithms, including the neural network algorithms, has been used with good results for minimizing variations and optimizing battery state of charge resulting in fluctuation suppression rate of 30% than traditional approaches [41]. model-based and learning-based hybrid control techniques are less computation demanding compared to classical control methods and that they only need a few samples for near-optimal control [47].
Recent research on application of AI-based energy management strategies in microgrids have revealed that practical implementations of those systems have managed to cut operational costs and enhance energy saving as compared to heuristic techniques [48]. There are several issues associated with conventional control approaches, such as slow performance and inability to cope with new scenarios in real-time while working in conditions where the RES can change dynamically [27].
Traditional techniques may take longer time and more computational power for the optimization compared to the conventional technics improved with AI, and hence they can only be applied in non-real-time scenarios [49]. The comparative analysis of AI based control methods and the conventional control methods in energy storage systems imply that the AI based methods have shown enhanced performance and efficiency. Machine learning and neural networks, in particular, show higher performance in the control of energy flows and the improvement of the system's response. It is therefore useful to point out that the integration of AI is not a threat, but on the contrary, a transformational opportunity for optimizing energy storage systems where traditional methods have the frameworks created.

3. CONCLUSIONS AND FUTURE WORK

The article reviews quite literature while focusing on the role of AI in shaping renewable energy sources and their storage systems. AI has the merits of adapting variable control routine according to the system status. Thus, as the literature showed that the AI in RESs could increase the reliability, continuity and sustainability.
The conventional control approaches of RESs have served for very long time while enjoys the simplicity. However, the performance of these schemes suffers from slow response, large overshoots and deteriorate waveforms. Therefore, different AI-based control approaches are currently under survey for RESs. These AI-controller are expected to shape the fields of RESs.
Incorporating energy storage systems in RESs is a useful policy, some prospects like high costs of establishing these systems or other technological disadvantages cannot be unnoticed. Solving these dilemmas is critical to the advancement of renewable energy farms and their application. It is identified that though AI methods have better prospects in enhancing energy storage systems efficiency and reliability, there are limitations tied with computational cost and strong secondary data requirements.

Future work based on what we reviewed in this work should aim to:
Introduce new techniques that requires low time and less computational power for the optimization and cut operational costs and enhance energy saving in power systems. In future work comparative analysis of AI models should be made and the most efficient strategies of power stability should be determined. Deep learning, reinforcement learning and fuzzy logic can also be adopted in enhancing real-time control and fault detection in power systems. Predictive maintenance strategies to prevent loss of system downtime can be facilitated by AI, and improve system reliability. Examine some future research issues in AI in terms of particular components of power systems including smart grid optimization, integrating renewable energies, grid resilience and forecasting in energy markets. Look at how the availability, quality, and privacy of data support future research on AI and how power systems work.. Research the possibility that AI will be used to improve cyber security and reliability of future power systems. Explore sophisticated AI/ML approaches (e.g. reinforcement learning, federated learning, explainable AI) that are especially promising to power system application in the future.

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