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Reinforcement Learning-Based Unified Power Flow Controller for Stability Enhancement in Hybrid Renewable Energy Systems: A Comprehensive Review

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ABSTRACT:
The fast integration of renewable energy sources into today power systems has made quite a few issues around voltage stability, frequency regulation reactive power control,and just overall grid dependability. Hybrid Renewable Energy Systems, maybe HRES , and especially ones that match wind energy conversion systems with diesel generators, have appeared like a solid option for keeping power coming in a continuous, and sustainable way. Yet the breaky, intermittent nature of renewables causes operational uncertainties that need advanced control methods. Flexible AC Transmission System devices, commonly called FACTS, especially the Unified Power Flow Controller, or UPFC, have shown notable promise for better power quality, steadier voltage, and improved power flow steering. Lately, Reinforcement Learning, RL, has drawn a lot of interest as an intelligent control approach that can adjust to shifting operating situations without needing perfect mathematical models of the system. This review aims to gather and discuss what has recently happened in renewable energy integration, ways to strengthen power system stability, FACTS controller applications, and RL based control approaches. It also looks closely at the existing work on voltage stability evaluation, transient stability enhancement, demand response optimization, energy management, and more intelligent UPFC control. In addition, the benefits, constraints, and open research gaps tied to traditional techniques versus AI based control are covered. In the end, the review points out that merging RL with UPFC looks promising for adaptive power flow control, reactive power compensation, and stability improvements within power systems that include renewables. Future research directions are also brought forward, so smart grid infrastructures can become more intelligent, resilient, and sustainable as renewable penetration keeps increasing.
Keywords: Hybrid Renewable Energy Systems (HRES), Reinforcement Learning (RL), Unified Power Flow Controller (UPFC), Flexible AC Transmission System (FACTS), Power System Stability, Renewable Energy Integration.

1. INTRODUCTION

The global requirement for electrical power has moved up quite a bit, thanks to swift industrialization, growing cities, population expansion, and continuous technological progress. At the same time, worries about environmental contamination, greenhouse gas emissions, and the diminishing supply of fossil fuel resources have pushed the shift toward renewable power generation even faster. Renewable resources like wind energy, photovoltaic energy, water based hydropower, organic biomass, and geothermal heat have shown up as stable substitutes for older conventional electricity methods. Among them, wind power has gotten a lot of attention , because it is widely accessible, relatively eco-friendly, and the setup costs keep falling. Still, when renewable generation is rolled into today's electric grids at large scale, it creates multiple engineering issues tied to power quality, voltage control, maintaining frequency stability, and regulating power flow, all together. Hybrid renewable energy systems, often shortened to HRES , are widely viewed as a practical way to boost reliability and efficiency in renewable power generation. In general these setups merge several energy sources like wind turbines, solar photovoltaic panels, diesel generating sets, plus some kind of energy storage devices so the output stays steady and dependable [1]. Wind energy conversion systems, especially those using Permanent Magnet Synchronous Generators (PMSGs), have shown strong efficiency with good operational flexibility inside hybrid arrangements. Diesel generators are frequently used as a secondary power option to keep everything reliable when renewable availability drops during low resource periods. Even so, HRES brings multiple technical, economic, and environmental benefits, the coordination and control across the different generation units is still hard, especially when the system keeps changing its operating conditions. The growing adoption of renewable energy sources matters a lot for how power systems move and react dynamically. Unlike classic synchronous generators, these energy resources come with power output that keeps changing, and it depends on weather, time , and other outside factors . Because of that, the system can face voltage instability, shifts in frequency, a mismatch in reactive power balance, and even transmission congestion. Voltage stability becomes a key need to keep acceptable voltage levels across the whole grid, both during usual operation and under disturbed conditions [2].

This figure 1 illustrates the main components of an electric power system, including generation, transmission, distribution, and end-user consumption, showing the flow of electrical energy from power plants to consumers.

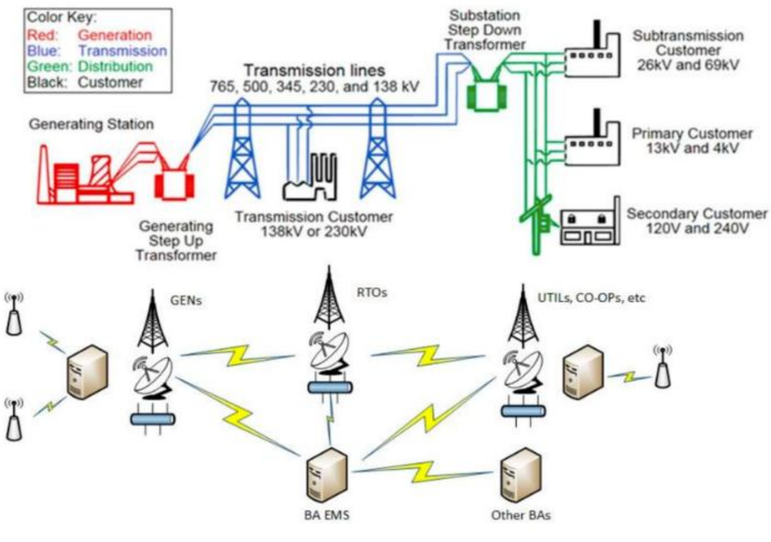

Figure 1: Typical structure of an electric power system [2]

To deal with these challenges, Flexible AC Transmission System (FACTS) devices have been widely used in today's power networks. In practice, FACTS controllers are advanced power electronic tools meant to enhance transmission system controllability, keep voltage in check, raise power transfer capacity, and support overall system stability. They give fast and adjustable supervision over transmission line parameters, including voltage level, line impedance, and phase angle.

Some usual FACTS units are Static VAR Compensators (SVC), Static Synchronous Compensators (STATCOM), Thyristor Controlled Series Capacitors (TCSC), Static Synchronous Series Compensators (SSSC), and Unified Power Flow Controllers (UPFC). Among these options, the Unified Power Flow Controller is often seen as one of the most adaptable and effective FACTS devices, because it can manage active power flow at the same time, handle reactive power compensation, and also regulate the bus voltage [3]. The Unified Power Flow Controller brings together what series compensation does and what shunt compensation does, within one single device, using two Voltage Source Converters VSCs, joined through one shared DC-link. In practice, that setup lets the operator manage voltage magnitude, phase angle and even the transmission line impedance in a fairly separate way, so the controller delivers broader power flow supervision, not just one narrow task. UPFC has been put to work in multiple power system cases, for example improving voltage stability, handling congestion, cutting losses, strengthening transient stability, and helping with renewable energy integration. Also, UPFC can react quickly when the grid faces disturbances, so it fits well for hybrid renewable energy arrangements, where the generation keeps varying and the operating point changes dynamically. Even with these benefits though, the actual impact of UPFC really hinges on how good the control strategy is.

Conventional UPFC control methods are usually built around proportional-integral, proportional-integral-derivative, fuzzy logic, neural network, or optimization based strategies. Even if these approaches have shown pretty good results when operating points are known in advance, the performance can drop when system parameters shift a lot or when the uncertainties tied to renewable energy generation start getting larger. As a result there is an increasing demand for smart, adaptive control schemes that can learn suitable control moves in real time, still keeping stability and operational efficiency in place. Recent progress in Artificial Intelligence (AI) together with Machine Learning (ML) has opened new chances for intelligent power system governance. Between different AI methods, Reinforcement Learning (RL) looks like a very useful approach for dealing with tangled decision, and control issues [4]. Reinforcement Learning lets an agent figure out better control strategies by communicating again and again with the environment, and it does not need labeled datasets, nor does it require a precise system model. The whole learning routine is steered by reward signals, which judge how effective each action is when the agent acts. By doing trial and error interactions, the agent keeps raising its decision abilities, even while the system conditions shift over time. In power system applications, Reinforcement Learning has been used pretty well for voltage regulation, frequency management, economic dispatch, energy supervision, demand response optimization, and power flow regulation. There are several reinforcement learning techniques, like Q-Learning, Deep Q-Networks (DQN), policy gradient methods, and deep reinforcement learning (DRL), that have shown a real chance to boost system adaptability, sturdiness, and operational efficiency. What makes RL based control a bit different is that it can learn directly from how the system behaves, and that part feels especially useful when controlling FACTS devices inside renewable energy integrated power networks. If the controller keeps updating its actions as network conditions change, then RL based UPFC controllers can help improve voltage stability, strengthen reactive power compensation, tune power flow, and raise overall system reliability. The increasing attention for intelligent control methods has led to many studies looking at how Reinforcement Learning can be merged with FACTS devices and renewable energy setups. Earlier work showed RL driven control strategies can help with transient steadiness, reduce power oscillation ringing, keep voltage patterns more controlled, and also improve how energy is scheduled or balanced [5]. Even so, issues tied to computational heaviness, scaling up, real time execution, and real world deployment still remain in active investigation. Also, broad surveys that specifically discuss the use of Reinforcement Learning with UPFC for stability improvement in hybrid renewable energy systems feel rather uncommon and not enough in number. So, this review paper presents a rather comprehensive analysis of recent progress in hybrid renewable energy systems and things related to power system stability enhancement, plus FACTS controller applications. It also looks closely at control strategies that use Reinforcement Learning, where the focus is on operational principles, but also on how these ideas get applied in real settings. For instance, the paper examines the UPFC and discusses different Reinforcement Learning techniques that have been used for power system control. At the same time, it critically evaluates what earlier studies have contributed, and where they fall short, which makes the discussion more useful than only listing methods. Moreover, it identifies current research gaps, existing limitations, and future directions, giving insights for researchers, engineers, and policymakers who are working toward intelligent, reliable, and sustainable power systems. Overall, the results of this review are expected to help push forward smart grid technologies and support the reliable integration of renewable energy resources into the electrical networks that will come next [6].

2. HYBRID RENEWABLE ENERGY SYSTEMS AND POWER SYSTEM STABILITY

Hybrid Renewable Energy Systems HRES have become a good, useful approach for dealing with the growing need of sustainable dependable and environmentally mindful electricity production. As fossil fuel resources keep getting used up, and worries about greenhouse gas emissions keep growing, renewable energy technologies are being taken up faster around the world. But wind power and solar power are naturally uneven, and they rely on surrounding conditions, so using them alone is not enough if the goal is steady ongoing supply. So, a hybrid setup blends different energy streams, such as renewable generators along with conventional backup generators and also energy storage, this is done to raise system reliability, add operational flexibility, and boost energy efficiency. Within the different hybrid layouts, pairing wind energy conversion systems with diesel generators has been getting major attention for both grid-connected cases and standalone setups. Even with all the benefits, bringing these pieces together can create technical obstacles, for example power quality issues, voltage stability concerns, frequency regulation, and doubts about the overall system reliability [7].

WECS, Wind Energy Conversion Systems, are a crucial part of today's hybrid renewable energy systems, because wind power is one of the fastest growing renewable energy technologies on the planet. In general, wind turbines take the kinetic energy of air that's moving and turn it into mechanical energy, then that mechanical output is changed into electrical energy by electric generator units. Out of these, PMSG based wind turbines have become widely used, not just for efficiency but also for less routine maintenance, plus their ability to keep running in real time even when wind speed changes a lot, which is common. With advanced power electronic converters in place, these generators can deliver steadier, higher quality electricity while still staying compatible with the grid, and the whole setup works more reliably overall. Even with their advantages, wind energy conversion systems still show some fairly big operational issues. Variations in wind speed directly drive the power level, and that leads to changes in voltage magnitude, system frequency, and also in power transfer. If the wind conditions shift quickly, power imbalances can show up and then they may harm stability as well as reliability. In bigger, wind-integrated power grids, these swings can bring voltage instability, frequency deviations, higher transmission losses, and weaker power quality. Also, wind turbines usually provide less inertia than traditional synchronous generators, so the overall dynamic stability of the grid becomes less robust. Because of that, it becomes necessary to use effective control plus compensation methods, so the hybrid energy system with wind stays in stable operation [8].

Diesel Generator Systems keep showing up as a big part of hybrid renewable energy setups, mostly because they can step in with backup power when renewable output drops low . Diesel generators tend to be used a lot due to their dependable operation, fast response, and the fact that they can deliver electricity without depending on weather conditions. In remote regions isolated communities, industrial locations, and islanded microgrids, diesel generators often end up being the main source of power that can be scheduled or dispatched. In hybrid renewable energy systems, they also help cover the intermittency of renewable resources, and they make it easier to keep electricity generation matched to actual load demand.

Putting diesel generators together with wind energy setups improves the overall system reliability and keeps things running without too much interruption. When there is enough wind around, renewable sources can cover a large share of the electrical demand, which means less fuel use and lower operating costs tied to diesel production [9]. But when the wind output drops because of bad weather, diesel units can quickly raise their output, so the power stays on and uninterrupted. This back and forth arrangement supports energy security, and it helps keep system behavior steady. Still, going between renewable and diesel more often creates extra control headaches, like how the load is shared, frequency regulation, voltage coordination, and even fuel optimization. For that reason, strong energy management approaches are needed to reach best use of hybrid renewable energy systems. Wind turbines along with power electronic converters , plus shifting operating modes, play a part in these issues, especially when the transmission or distribution network is weak. Voltage stability is a big, important topic for how power systems actually run when there are renewables involved. In general, voltage stability is about how well a power network can keep voltages at acceptable levels on every bus during regular operation and also after disturbances. So, more advanced compensation devices, and smarter control methods are needed to keep the whole network's voltage profile stable. Frequency stability is basically the ability of a power grid to stay in equilibrium, between generated power and consumed power, after disturbances happen. If there is any mismatch between generation and load, the system frequency can drift, and this can hurt the behavior of electrical equipment, and also the protection schemes, sometimes at the same time [10].

Reactive power management also plays a vital role in keepin g stable and efficient operation of hybrid renewable energy systems, somehow. Reactive power is needed for holding voltage levels in place, and to support the electrical equipment during day to day operation. With renewable energy in the mix, the need for reactive power support frequently rises, because generation patterns keep changing and load conditions are never truly steady. So advanced power electronic compensation devices, plus intelligent control methods, are being used more and more, to strengthen reactive power handling and to raise overall system performance. The increasing complexity in hybrid renewable energy systems has made it pretty clear that advanced monitoring, control, and optimization are not optional. In modern power grids, there is a need for intelligent solutions that can change with shifting operating conditions, while still holding the line on voltage stability, frequency regulation, and acceptable power quality levels. A range of approaches is now showing up as promising tools, for example Flexible AC Transmission System (FACTS) devices , energy storage systems, machine learning algorithms, and reinforcement learning based controllers. These tools bring better system observability, more adaptive control actions, and higher quality decisions overall. As a result the integration of renewable energy resources becomes more efficient, and less brittle to disturbances [11].

Overall, hybrid renewable energy systems that fuse wind energy conversion systems with diesel generator technologies do offer a practical and dependable approach for producing reliable, and sustainable electrical power. Still, because the renewable side is intermittent there are substantial problems tied to power quality, voltage stability, frequency handling and reactive power supervision. Tackling these issues means using advanced control strategies plus intelligent system management methods that can keep the whole setup steady and efficient, even when the surroundings and load vary. As renewable energy penetration keeps climbing worldwide, guaranteeing the stability and reliability of these hybrid systems will stay an essential research and development focus for the future electrical grids.

3. FLEXIBLE AC TRANSMISSION SYSTEM (FACTS) CONTROLLERS

So yeah the rapid growth of electrical power networks and the stronger integration of renewable energy resources have brought some serious challenges for today power system operation, and not just one thing either. At the same time, electricity demand keeps rising, transmission paths get jammed, voltage can become unstable, reactive power balance goes off, plus the renewable generation keeps swinging around in time. But the older methods, like expanding transmission lines or building new generation facilities, often require heavy financial investment, they raise environmental concerns, and the implementation timelines can take quite a while. So in response power system engineers have started to use the existing transmission infrastructure in a more effective way, using advanced power electronic technologies, not just adding more hardware. Flexible AC Transmission System (FACTS) controllers have, at this point become one of the most useful solutions. They help enhance transmission network performance, they improve power quality, and they support system stability when the operating conditions change dynamically.

FACTS technology was developed to deliver fast flexible control of power system parameters, through the use of high-power semiconductor parts and advanced control approaches. The main purpose of FACTS devices is to raise the controllability and the power transfer capacity of AC transmission systems, while keeping secure , and steady operation. These controllers tune key transmission quantities like voltage magnitude, transmission line impedance, and also phase angle, which lets operators manage active power along with reactive power in a more effective way. Because they react quickly to shifting system situations, FACTS devices support better voltage regulation, improve both transient stability and steady-state stability, cut transmission losses, and strengthen overall system dependability. In practice the use of FACTS controllers is especially important in power systems that integrate renewable generation, where the variation in power output and the inherent uncertainty can seriously disturb system performance. One big advantage of FACTS technology is that it can enhance transmission line utilization, without needing more physical infrastructure. In conventional transmission systems, the power flow is determined mostly by the network characteristics and the operating conditions, so operators have less flexibility to manage how the system behaves. With FACTS controllers, those limitations get reduced because they can dynamically tune electrical parameters, to nudge power flow toward an optimal path and boost network efficiency. Because the response is fast [12]-[13], they can also react effectively when the system gets disturbed, like during faults, sudden load variations, or even quick fluctuations coming from renewable generation. So, these FACTS devices help a lot with keeping acceptable voltage profiles, easing congestion, damping oscillations, and avoiding voltage collapse when the grid is under stressed operating conditions.

FACTS controllers can be sortof placed into a few groups, depending on how they connect and what kind of control it does. The most used groups are shunt-connected controllers, series-connected controllers, combined series-series controllers, and combined series-shunt controllers. Every group tends to do its own tasks, and it brings distinct advantages, depending on the needs of the whole system. For instance, shunt-connected FACTS devices are tied in parallel with transmission lines and mainly deal with reactive power compensation plus voltage support. Some familiar examples are the Static VAR Compensator (SVC) and the Static Synchronous Compensator (STATCOM). These devices help regulate bus voltage by injecting reactive power or taking it away, so voltage stability improves and transmission losses can go down. Because their response is fast, they tend to work very well in situations where voltage keeps swinging, due to changing load conditions, or when renewable energy is being integrated into the grid. Series connected FACTS controllers are placed in series with the transmission line, and they are usually for controlling line impedance , and also power flow. Stuff like the

Thyristor Controlled Series Capacitor (TCSC), Thyristor Controlled Phase Shifting Transformer (TCPST), and Static Synchronous Series Compensator (SSSC) fall into this group. [14].

Combined series-series FACTS controllers use several series connected converters that work together, in a coordinated fashion, to handle power flow more broadly. They let operators manage power transfer on different lines at the same time and they also make the network more adaptable. Even if they are not as frequently used as shunt and series controllers, the combined series-series arrangement is still pretty valuable in tricky transmission systems where advanced power flow management is needed. Because the converters coordinate their actions, the system can optimize network performance, and at the same time it can reinforce stability and reliability.

The most advanced category of FACTS technology is made up of combined series-shunt controllers, which basically bring together both series and shunt compensation in one single device. This arrangement gives control over voltage magnitude, line impedance, and phase angle at the same time, so it delivers a higher degree of flexibility plus more manageable behavior than many other FACTS units. The Unified Power Flow Controller UPFC is likely the most visible and most frequently studied device in this group. Because it can independently steer several power system variables, the UPFC is frequently viewed as the most capable FACTS controller that we can use in today's transmission networks.

The Unified Power Flow Controller came in to beat the shortcomings of standalone FACTS equipment, by putting together the shunt and series compensation roles in one compact thing. The UPFC is built from two Voltage Source Converters (VSCs) that share a common DC-link capacitor, so they stay tied together in that way. Usually, one VSC works as a shunt compensator, while the other VSC acts like a series compensator.

For the shunt side, the converter gets linked to the transmission network via a shunt transformer, and it handles several tasks at once: it regulates the bus voltage, keeps the DC-link voltage stable, plus it offers reactive power compensation. On the series side, the converter goes through a series transformer and then injects a controllable voltage into the transmission line, in order to steer the active power and reactive power flow. Because both converters share the same DC-link, there is a workable power exchange between them, which helps coordinate control actions and also lets them be adjusted separately when needed. The UPFCs unusual structure lets it do, at the same time, several FACTS device tasks including STATCOM, SSSC, and phase shifting transformers. Because of this ability, it can handle power system operation more comprehensively and it gives real improvements in network behavior [15]-[16]. When the UPFC adjusts voltage magnitude, tweaks transmission line impedance, and sets the phase angle, it can steer both active power and reactive power flows to match what the grid needs. That kind of flexibility makes the device a great fit for renewable energy connection, congestion relief on transmission corridors, voltage steadiness enhancement, and also damping of oscillations.

A key use of the UPFC is for voltage stability improvement, and it works even when things get a bit messy. Renewable energy sources like wind and solar can cause swings in power production , which then may lead to voltage instability and a reactive power imbalance. The

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UPFC deals with this by continuously injecting or absorbing reactive power, so the voltage stays within acceptable limits across the network. Also, it can support transient stability, since it answers quickly when disturbances happen, and it helps the system return to equilibrium after faults or sudden load changes. Beyond that, the UPFC's power-flow regulation also tends to ease transmission congestion, and it improves network utilization, so the overall operation stays efficient. The efficiency of UPFC action depends a lot on how well the control strategy performs, at least in practice. Traditional control approaches, like Proportional Integral (PI) Proportional Integral Derivative (PID), fuzzy logic, and controllers that rely on optimization, have been used a lot in UPFC setups. Still, the modern grid is getting more complex day by day, and renewable energy resources are coming in with a faster pace, so it has pushed many researchers to look at more intelligent control techniques that can adjust to time-varying operating situations. Newer methods built on artificial intelligence, machine learning, and reinforcement learning have shown a real promise for better UPFC performance, improved stability margins, and for steering the power system toward an optimal operating mode [17].
In a nutshell, FACTS controllers have become kind of indispensable parts of modern electrical power systems , because they can lift transmission efficiency, help power quality, and also reinforce the overall stability of the grid. Among the different FACTS technologies, the Unified Power Flow Controller feels like the most capable and wide ranging device, since it can control voltage, impedance and also the phase angle all at the same time. Putting UPFC technology into practice has helped quite a lot with the smooth integration of renewable energy resources and with dependable day to day power network operation. Since power systems keep evolving toward smarter and more sustainable infrastructures, FACTS controllers, especially UPFC, will stay critical instruments for guaranteeing secure, adaptable , and high performance power system operation.

4. REINFORCEMENT LEARNING FOR POWER SYSTEM CONTROL

The growing complexity of current power systems, pushed by the big integration of renewable energy resources, distributed generation, smart grids, and advanced power electronic devices, has led to a stronger need for intelligent, adaptive control ways. Traditional control methods have been used a lot for keeping voltage stable, handling frequency regulation, managing power flow, and reactive power compensation. Still, these approaches often depend on exact mathematical models and fixed operating situations, which may not really capture how fast, and how uncertain, renewable energy integrated power systems can be. Fluctuations in wind speed, solar irradiance, load demand , and even the network topology bring in uncertainties that can influence the system behavior quite a bit. Because of that, many researchers started looking into artificial intelligence based techniques, to improve power system control and decision making. Within this group, Reinforcement Learning (RL) has become a promising method, because it can learn better control strategies by interacting with the environment and then adapting to new operating conditions without needing explicit system models. Reinforcement Learning is like a machine learning branch that aims to help an intelligent agent learn what actions to take by doing ongoing back and forth with its environment. Unlike supervised learning, which expects labeled training data , reinforcement learning uses a trial and error style process, where the agent figures things out from the outcomes of what it does . The whole learning routine is tied to maximizing the total rewards it gathers from the environment as time goes by. In a typical RL setup, the agent first looks at the environment's current situation, then it picks an action based on its policy, and it also gets a reward that points to how good that action was. After that, the environment moves on to another state, and the cycle keeps going over and over [18] . By doing many of these interactions, the agent slowly uncovers the most effective plan for reaching the target goals. Reinforcement learning's core parts are the agent, the environment, the state, the action, the reward, and the policy. Then actions are the actual control choices the agent gets to make, for example changing reactive power compensation, tweaking generator outputs, or operating FACTS devices. The reward function then judges how good each choice was, and it steers the training toward certain outcomes and targets, while also shaping the learning path. Finally the policy lays out the strategy the agent follows to choose actions from the observed state. In the end, reinforcement learning aims to find an optimal policy, one that maximizes long-term cumulative rewards while still keeping the system steady and performing well.

One of the earliest and most commonly used reinforcement learning algorithms is Q-Learning . It is a model-free learning approach that helps an agent learn the usefulness of choosing certain actions in specific states , without needing prior knowledge about how the environment dynamics behave. The method leans on a Q-value function, which people also call the action-value function , to approximate the expected long term reward tied to each state and action. While training, the agent keeps adjusting the Q-values using the rewards it notices, plus the outcomes that come next. Eventually, these Q-value estimates tend to settle near the best values, and then the agent can choose actions that maximize the expected reward.

Q-Learning stays popular because it feels simple, it is easy to implement, and it can handle sequential decision tasks without too much fuss. In power system use cases [19], Q-Learning has been used well for voltage control, frequency regulation, demand response coordination, and energy storage optimization. Through ongoing interaction with the power system environment, Q-Learning agents manage to learn useful control strategies that raise operational efficiency while also supporting system stability. Still, the usual Q-Learning method hits major roadblocks when the power system gets large, especially when the state space becomes high-dimensional and the action space also grows. Once the amount of states jumps, the memory demands for the Q-table and the computation needed become too heavy, and that makes the overall scalability of the algorithm harder to maintain.

To tackle these limitations, researchers have been developing Deep Reinforcement Learning, or DRL, a mix of reinforcement learning ideas and deep neural networks. DRL relies on artificial neural networks to estimate value functions, plus policies, so the system can learn more efficiently in complicated, high dimensional spaces. Rather than keeping results in massive lookup tables, the DRL approach learns a kind of generalized representation of how a system behaves, through the training of the neural network. Because of this, DRL methods can manage large scale power systems, with many state variables, and lots of possible control actions. One of the most influential DRL approaches is the Deep Q-Network (DQN) . It uses deep neural networks to approximate Q values for various state action combinations, and this is pretty central to how it learns. In practice, DQN can boost scalability and learning potential compared with standard Q-Learning, mainly because it can deal with big datasets and messy system dynamics in a more efficient way, or at least that is what people often report. There are also several other DRL directions, like Deep Deterministic Policy Gradient (DDPG) , Proximal Policy Optimization (PPO) , Actor Critic methods , and Twin Delayed Deep Deterministic Policy Gradient (TD3). Together, these newer schemes have improved reinforcement learning results, especially in continuous control settings. Overall, the more advanced algorithms tend to bring better learning efficiency, quicker convergence, and stronger flexibility when operating conditions keep shifting. Reinforcement learning in power systems has been expanding fast in the last few years, mostly because it can handle tangled control and optimization problems, in a more responsive way. A big use case is voltage regulation along with reactive power control. Keeping voltage levels steady matters a lot, for reliable power system work, especially in grids that have a high share of renewable energy [20]. In this setting reinforcement learning controllers can keep an eye on what is happening in the system all the time, and figure out suitable reactive power compensation actions, so the voltage stays stable. And since RL agents learn from how the system reacts in real time , they can adjust to changing operating conditions more effectively than many traditional controllers.

Frequency regulation is another pretty vital application field for reinforcement learning. Since renewable energy generation is intermittent , it often causes power imbalances and these end up as frequency deviations. RL based controllers can dynamically align generation assets, energy storage units, and shiftable demand to keep frequency inside allowable bounds. With ongoing learning and adjustment, the same controllers deliver fast and useful reactions to disturbances, so the whole power system becomes more trustworthy and tough under stress.

Reinforcement learning has also showed a lot of ability in energy management systems. These days power networks more and more use intelligent energy management methods to help with resource utilization, lower the operating costs and raise energy efficiency. Because of this, distributed energy resources can be coordinated much more efficiently while system stability and reliability stay under control [21]. Another key use of reinforcement learning is in power flow optimization and the whole transmission system control part. Using RL-based methods, the system can try to learn good strategies for managing transformer tap changers , capacitor banks, and also the Flexible AC Transmission System, also called FACTS equipment like Static VAR Compensators, which are SVCs , Static Synchronous Compensators or STATCOMs, and Unified Power Flow Controllers, known as UPFCs. As the environment changes, reinforcement learning keeps tuning control parameters according to current grid conditions, so the learning process tends to push higher power delivery capability , lower transmission losses, and better voltage stability overall.

Furthermore, reinforcement learning has been successfully applied in micro grid operations , and also for demand response management , fault detection, protection coordination, plus renewable energy forecasting. In smart grid environments, RL enables autonomous decision making and adaptive control, and it helps with integrating huge sets of distributed energy

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resources. These benefits are especially valuable for future power systems that feature more decentralization, deeper digitalization, and higher levels of renewable energy penetration [22]. On top of that, making sure the learning process is both safe and reliable in actual power grids still counts as a major research topic. Even so, the continuing progress in computing tech, artificial intelligence, and smart grid infrastructure keeps making RL based control solutions more achievable. Table 1 presents a comparative review of recent studies on renewable energy integration, FACTS controllers, and reinforcement learning-based power system control, highlighting their methodologies, key contributions, results, and research limitations for enhancing power system stability and reliability [23].

Table 1: Comparative Literature Review of Renewable Energy Integration, FACTS Controllers, and Reinforcement Learning-Based Power System Control

Ref.	Objective	Methodology/Algorithm	Key Contribution	Results	Limitations
[1]	Assess voltage stability in wind-integrated power systems	Noise-resilient CNN	Developed deep learning-based voltage stability assessment model	Improved voltage stability prediction accuracy	Limited to static stability assessment
[2]	Enhance grid stability and renewable integration	Reinforcement Learning	Proposed RL-based demand response framework	Improved grid stability and renewable utilization	Lack of real-time validation
[3]	Evaluate probabilistic stability under uncertainty	Physics-Informed Neural Network (PINN)	Integrated physical constraints with neural networks	Enhanced stability assessment reliability	High computational complexity
[4]	Coordinate source-grid-load-storage dispatch	Data-driven dispatch strategy	Improved coordination among energy resources	Increased operational efficiency	Data dependency issues

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[5]	Enhance transient stability in wind systems	Multi-Input Backstepping Control with UPFC	Improved transient stability using UPFC	Better damping and faster recovery	Simulation-based validation only
[6]	Design optimal hybrid renewable energy system	Optimization technique	Developed optimal PV/Wind/PHS configuration	Improved reliability and energy continuity	Site-specific applicability
[7]	Assess transient stability	DASeq2Seq with branch potential energy method	Combined deep learning with energy-based analysis	Improved assessment accuracy	Limited test case evaluation
[8]	Improve reliability through RES integration	Optimization-based approach	Enhanced reliability indices	Improved system resilience	Economic factors not considered
[9]	Evaluate marine renewable energy contribution	Complementary energy analysis	Assessed balancing capability of wave and tidal energy	Reduced intermittency effects	Limited geographical analysis
[10]	Analyze AGC challenges in renewable grids	Review study	Identified AGC challenges and future directions	Highlighted advanced control requirements	No practical implementation
[11]	Assess stability issues with high RES penetration	Comprehensive review	Reviewed stability assessment and mitigation methods	Identified major stability concerns	Lacks quantitative analysis

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[12]	Mitigate renewable power variability	Hydrogen energy storage	Utilized hydrogen storage for grid support	Improved stability and renewable utilization	High infrastructure cost
[13]	Analyze climate change impacts on power systems	Review and assessment	Evaluated resilience factors and adaptation strategies	Identified climate-related risks	Limited practical validation
[14]	Review voltage stability improvement methods	Literature review	Summarized monitoring and control techniques	Highlighted role of FACTS devices	No novel methodology proposed
[15]	Investigate impact of VPPs on grid stability	IoT-based framework	Integrated VPPs for improved grid management	Enhanced flexibility and stability	Cybersecurity issues not addressed
[16]	Improve grid resilience using BESS	Optimization techniques	Determined optimal BESS placement and sizing	Improved voltage regulation and reliability	Limited economic analysis
[17]	Analyze renewable integration challenges	Review study	Identified adaptation and modernization strategies	Improved understanding of grid stability	Region-specific findings
[18]	Investigate challenges of variable RES integration	Review analysis	Examined mitigation strategies	Identified operational challenges	Lack of experimental validation
[19]	Improve interarea oscillation damping	Deep Reinforcement Learning	Developed DRL-based damping controller	Enhanced dynamic stability	High computational burden

[20]	Review AI-driven FACTS control strategies	AI and ML techniques	Reviewed intelligent FACTS control approaches	Improved understanding of AI applications	No practical implementation
[21]	Generate optimal speed profiles	MPC with Reinforcement Learning	Combined MPC and RL for adaptive control	Improved tracking and efficiency	Limited to simulation environment
[22]	Develop cooperative robot control	Deep Reinforcement Learning	Enabled coordinated navigation and obstacle avoidance	Improved task performance	Not tested in large-scale environments
[23]	Predict PD controller gains	Reinforcement Learning	Optimized UAV controller parameters adaptively	Enhanced stability and maneuverability	Limited experimental validation
[24]	Optimize Organic Rankine Cycle operation	RL with GP-NARX models	Developed intelligent control framework	Improved efficiency and control accuracy	Computational complexity
[25]	Optimize variable speed limit control	Multi-Agent Reinforcement Learning	Implemented real-world RL-based traffic control	Reduced congestion and improved traffic flow	Domain-specific application

5. CONCLUSION AND FUTURE WORK

In this review, a somewhat comprehensive analysis about Hybrid Renewable Energy Systems (HRES), power system stability troubles, Flexible AC Transmission System (FACTS) controllers, and Reinforcement Learning (RL)-based control ideas has been put forward. It goes on and highlights how the growing importance of renewable energy integration brings along issues tied to voltage stability and also frequency regulation reactive power handling, and even the way power flow is directed. Among FACTS devices, the Unified Power Flow Controller (UPFC) shows up as an effective fix for boosting system stability and day to day operational flexibility. Also the RL methods,especially Deep Reinforcement Learning, have shown a clear promise for building adaptive intelligent control schemes for today's power systems. Even with all those advancements, some major obstacles still are there,like computational complexity, real time deployment, scalability ,and cybersecurity. For what comes next, future work should aim at fusing advanced RL algorithms with UPFC controllers, energy storage systems, and smart grid technologies, so the power system can run more reliably, resiliently, and sustainably even when renewable penetration is high.

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