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Reinforcement Learning Control Strategies for Virtual-Inertia Grid-Connected Inverters and Stability

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Abstract: As inverter based renewable energy increases, modern power systems are faced with reduced inertia which makes it a major source of concern in the frequency stability and the momentary performance. Inverters based on grid-forming inverter configurations with virtual inertia control have become a valid solution, and reinforcement learning is an adaptive optimization of control parameters, which operates in changing conditions. The control strategies-based on reinforcement learning of virtual-inertia enabled grid-connected inverters are examined in this review with focus on modelling technique, control design, and stability behavior. The literature is structured into four major themes, namely inverter roles in virtual inertia provision, modelling of grid-forming inverters and virtual synchronous generator control, reinforcement learning algorithms for adaptive inertia tuning, and system-level stability implications. Continuous action algorithms such as DDPG, TD3, and SAC are found to dominate current research, while recent studies increasingly explore multi-agent coordination, physics informed learning, and safe control frameworks. Although most studies show improvements in frequency deviation, reduced RoCoF, and settling time, fewer integrate classical stability analysis into reinforcement learning. The review highlights current research gaps, future opportunities for stability-oriented reinforcement learning control in low inertia power systems.

Index Terms: Adaptive Control, Grid Forming Inverters, Low Inertia Grids, Reinforcement Learning, Virtual Inertia.

1 INTRODUCTION

The global shift to renewable energy sources, including solar photovoltaic (PV) and wind generation, has significantly transformed the structure and design of the modern power system, with the power electronic converters [1]. Unlike traditional synchronous generators, renewable energy sources are linked to the grid. These inverter-based resources are very flexible and efficient, but they lack the mechanical inertia generated by the conventional generators. As a result, the contemporary power systems have a low-inertia effect, which results in rapid variations in Rate of Change of Frequency (RoCoF), and lack of stability during the fluctuations [2].

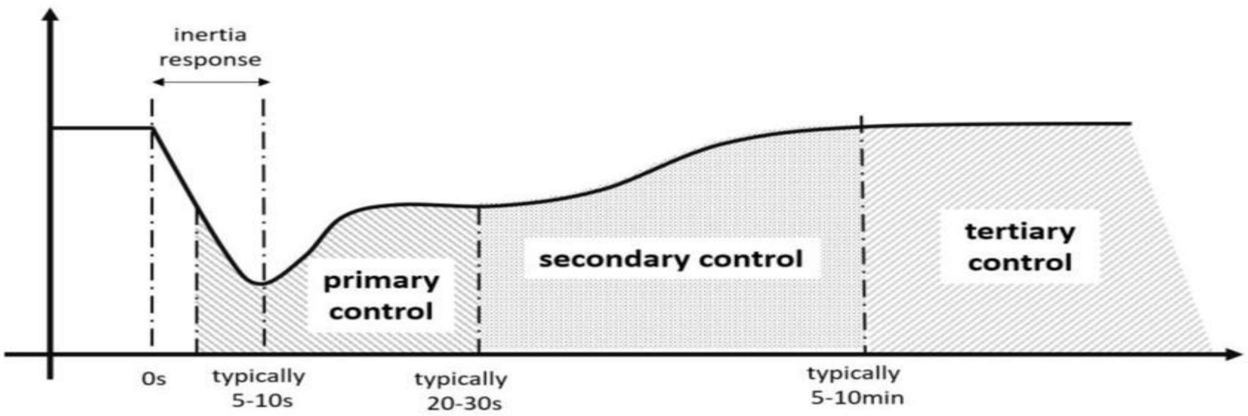

Fig. 1. Frequency Deviation during a disturbance

Fig.1 shows how the frequency fluctuations happen during a disturbance. When a sudden load shedding or a generator Outage causes an imbalance between generation and demand, this deviates the nominal system frequency from 50Hz. To prevent the frequency from going to very high or a low value synchronous generators supply the stored kinetic energy, which slows down the RoCoF.

To solve this problem, the notion of virtual inertia has been offered. The behavior of power electronic inverters that mimics synchronous generator behavior to frequency deviations is referred to as virtual inertia. The grid-forming inverters (GFM), virtual synchronous generators (VSG) and synchronverters are some of the methods that have been explored widely to offer synthetic inertia services in inverter-dominated power systems. These methods improve the stability of frequencies by minimizing RoCoF and the dynamic performance [3].

Virtual inertia is a control tool that is aimed at mitigating the decrease in rotational inertia that occurs in current power systems with high shares of renewable energy. In a traditional power grid system, the rotating mass of the system depends on the rotating generators to provide natural inertia to counteract unexpected changes in the frequency of the system during disturbances. Using contrast, much of the renewable generation, such as solar PV and wind turbines, is linked to the transmission system through power-electronic transformers which do not necessarily offer mechanical inertia. This way, inertia of the aggregate system is reduced, promoting more frequency oscillations and reduced stability in frequencies [4], [5]. Virtual inertia aims to emulate the inertial response of synchronous generators using advanced control algorithms in power-electronic converters. Virtual inertia can stabilize frequency of power systems by modulating inverter-based resource active-power output proportionally to frequency deviation or RoCoF and improve the dynamic capability of low inertia power systems.

Over the past years, reinforcement learning (RL) has become an effective and versatile control approach to dynamic and uncertain systems. RL-based controllers can be trained to work out the best control policies by walking around the system and do not need an explicit mathematical model. Deep Deterministic Policy Gradient (DDPG), Twin Delayed Deep Deterministic Policy Gradient (TD3), Soft ActorCritic (SAC) and Q-learning algorithms have been used on grid-connected inverters with virtually inertia-controlled virtual inertia. Through these methods, the control parameters such as virtual inertia and damping coefficients can be adaptively changed to enhance frequency regulation and stability of the system under a wide range of operating conditions [6], [7], [8].

Fig.2 illustrates how the virtual inertia concept has been developed throughout the years with the RL techniques.

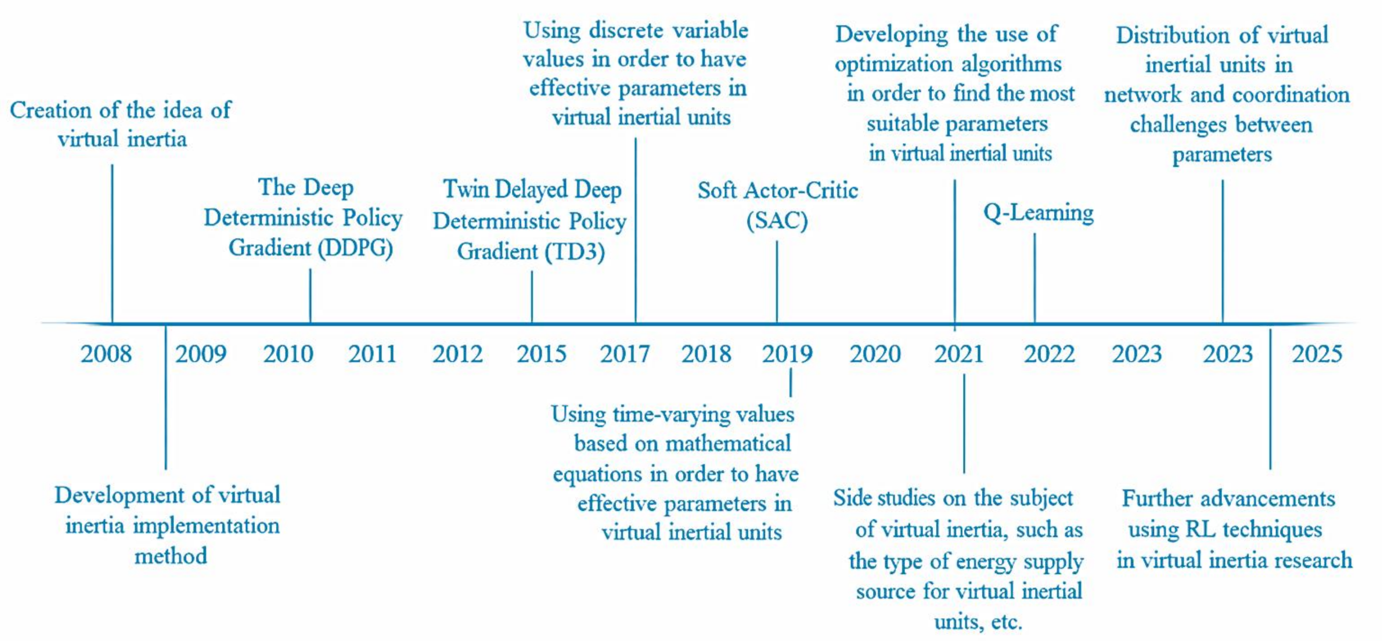

Fig. 2. Timeline of the virtual inertia concept development

Various RL-related virtual inertia control studies have already been published in the most recognized academic journals and conference papers, such as IEEE journals, international conference papers, peer-reviewed journals available on databases like IEEE Xplore, ScienceDirect, Springer, and MDPI. Literature contains an extremely broad spectrum of inverter schemes, control schemes, and reinforcement learning algorithms. The systematic review of the existing research is thus highly important to generalize the information and determine the most important progress in the given direction.

The current review article provides a survey of about 51 research articles such as journal articles, IEEE conference papers, and technical reports on reinforcement based -learning virtual inertia control through grid connected inverters. The chosen studies are rationally classified based on the type of inverter, control structure, reinforcement learning, and application conditions. The review also compares methods and performance indicators of various approaches, identifies gaps in the research, and suggests alternative research directions to stabilize and control the frequency of low-inertia power systems.

2 METHODOLOGY

2.1 Paper Selection Criteria

To make sure that the quality and relevance of the literature reviewed are of high value, a systematic paper selection procedure was performed. First, 65 research articles were identified in the leading scholarly databases such as IEEE Xplore, ScienceDirect, and Google Scholar with the keywords: virtual inertia, reinforcement learning, grid -forming inverters, and frequency stability. After a preliminary selection of titles and abstracts, some papers were filtered out based on a lack of direct interest in virtual inertia control, insufficient emphasis on reinforcement-learning methodologies, and duplication in databases. Also, literature that focused mainly on the general stability of power systems without discussing inverter-based virtual inertia or reinforcement-learning algorithms was excluded.

Upon implementing such inclusion and exclusion criteria, it was determined that 51 articles would be analyzed in detail in this review. The resulting corpus consists of a collection of peer-reviewed journal articles, IEEE conference papers, etc. high-quality research publications that concentrate on reinforcement-learning-based virtual inertia control in power systems dominated by inverters.

2.2 Paper Classification Method

The selected papers were then filtered according to the following topics: virtual inertia and inverter roles, inverter modelling, RL control formulations and algorithms, system impacts challenges and future impacts. This classification allows for a systematic comparison of various research methodologies and highlights significant advances in reinforcement learning-based virtual inertia control. Furthermore, it aids in identifying current research gaps and prospective future research objectives for increasing frequency stability in renewable-dominated power systems. Based on the above classification Table 1 summarizes the classification of reviewed literature.

Table 1 Classification of reviewed papers about virtual inertia and RL algorithms

Category	Example Paper	Inverter Type	Control Strategy	RL Algorithm	Application
Generator emulation control	[9]	PV inverter	Generator emulation control	—	Grid support
Impact of renewable penetration	[10]	Inverter-based RES	Frequency stability analysis	—	Frequency response
Inertia estimation methods	[11]	Power system level	Inertia estimation	—	Low-inertia systems
Deep RL control for VSG	[12]	VSG	Adaptive inertia control	Deep policy gradient	Frequency stability
RL-based inverter control	[13]	Grid-forming inverter	RL-based control	Deep RL	Oscillation suppression
SAC-based VSG parameter control	[14]	VSG	Adaptive parameter tuning	SAC	Frequency control
MADDPG-based inertia damping	[15]	VSG	Adaptive inertia damping	MADDPG	Stability improvement
Multi-agent RL inertia-droop control	[16]	Multiple VSG	Distributed inertia-droop control	SAC	Oscillation damping
Q-learning synchronverter control	[17]	Synchronverter	Adaptive virtual inertia	Q-learning	Microgrid stability
Physics-informed RL for VSG	[18]	Grid-forming inverter	Physics-embedded RL	RL	Transient stability
Learning-based predictive inertia control	[19]	Inverter-based generation	Predictive virtual inertia	Learning-based	Frequency regulation

3 MODELLING FOUNDATIONS OF VIRTUAL INERTIA

3.1 Frequency Dynamics in Low Inertia Systems

As it has been pointed out earlier in the introduction, the behavior of the power system frequency that is dynamic is largely determined by the rotational inertia of the system. In traditional power systems, the kinetic energy is stored in huge rotating masses and then used to offset sudden changes in load or to offset an outage by a generator, which reduces the transient RoCoF events and allows the recovery time to restore the normal frequency value [20].

On the other hand, the modern power systems are becoming increasingly equipped with renewable energy resources such as photovoltaic and wind generation which are not linked to the rotating machine but linked to the power electronic converters [21]. Resources based on inverter do not have any mechanical inertia therefore reducing the bulk response of the system due to inertia. It may cause an increase in the frequency deviation rate and high RoCoF when it is disturbed, which challenges the system stability, protection, and reliability.

The implications of decreased inertia in renewable-based power networks have been studied in several works. Several research have been conducted on the impact of lower inertia in power systems based on renewable sources. Indicatively, [10] researched the effects of large penetration of renewable energy sources on frequency behavior and indicated that low inertia of the system leads to high RoCoF, and lower margins of frequency stability. Equally, [11] emphasized the significance of precise inertia prediction and forecasting techniques in the pursuit of running the future low-inertia power systems. These results have underlined the importance of new control measures that can replace the natural inertia of the current power grids.

3.2 Generator Inertia Mathematical Modelling.

The swing equation is a nonlinear bi-second order differential equation that summarizes rotor relative dynamics with a synchronously rotating reference frame. It forms the main analytical methodology of power system engineering to evaluate transient stability, to establish whether a generator will continue to follow the grid after a significant disturbance to it, such as a short circuit or transient surge load [22].

$$P_m - P_e = P_a = \frac{2H}{\omega_0}\frac{d^2\delta}{dt^2} \tag{1}$$

Equation 1 illustrates, inertia constant H is the kinetic energy of the rotating mass, which is stored, P_m and P_e are mechanical input power and electrical output power respectively. The damping coefficient D reflects the dissipative process which diminishes oscillations of the system. When a disturbance sets up a discrepancy between mechanical and electrical power the speed of the rotor varies, and hence the system frequency deviation is generated [23]. The swing equation shows that more inertial systems undergo lower frequency changes during the disturbances thus giving the control systems ample time to stabilize the grid and avoid failure of the frequencies. The opposite is true of low-inertia systems, which have strong frequency dynamics and therefore make the system more vulnerable to disturbances. A great number of modern methods of control of resources based on inverters rely on this classical model of generators. To illustrate, [12] have come up with a model of data-driven optimal control of virtual synchronous generators with reinforcement learning where the dynamics of an inverter were represented in terms of swing-based frequency models. Inverter control loops can achieve the effect of emulating inertial behavior in converter dominated power systems by implementing a form of generator like dynamics.

3.3 Virtual Inertia Control Strategies

Different control schemes have been developed to solve the problem of low system inertia so that the inverter-based resources can mimic the dynamic behavior of synchronous generators. This is generally known as virtual inertia where power electronic converters simulate the inertial response of rotating machines with a well-designed control software [24].

3.3.1 Virtual Synchronous Generator (VSG)

One of the simplest researched applications of virtual inertia is its implementation in a virtual synchronous generator (VSG). In VSG control, the inverter is coded to simulate electromechanical behavior of a synchronous generator by adding the swing equation (1) to the inverter control architecture. This allows the inverter to behave like traditional generators, offering inertial and damping responses, and enabling inverter-based resources to be used to add frequency control as well as make the system more stable in low-inertia grids. Several researchers have proposed better VSG control measures to enhance performance in the system. As an example, [25] presented a distributed inertia-droop control method of multi-paralleled VSG units to reduce the power fluctuations in multi-inverter systems. What their study shows is that through the synchronized manipulation of virtual inertia parameters, it is possible to enhance damping and stability of the system in a wide range of operating conditions.

3.3.2 Synchronverter

Other major implementations include the synchronverter that simply copies the electrical and mechanical properties of synchronous machines into inverter control algorithms. The synchronverter method models the parameters of the generators which include rotor inertia, electromagnetic torque and voltage dynamics. [16] introduced the adaptive synchronverter algorithm based on Q-learning that opens the way to optimizing virtual inertia parameters dynamically ensuring the best frequency stability compared to traditional control strategies.

3.3.3 Droop Control

Alongside VSG and synchronverter methods, droop control is a common type of regulation used in grid-forming inverters to share power and to adjust the frequency of distributed units of generation.

$$f = f^{*} - K_P(P - P^{*}) \tag{2}$$

Equation (2) explains the behavior of droop control. Droop control is a decentralized control law that links an inverter's output frequency to its active power output, mimicking the natural behavior of synchronous generators. When the inverter supplies more active power the frequency drops proportionally, and when it supplies more reactive power the voltage magnitude decreases proportionally [16]. This creates a voltage phasor that can share load with other converters without communication, providing momentary reserve and electrical inertia.

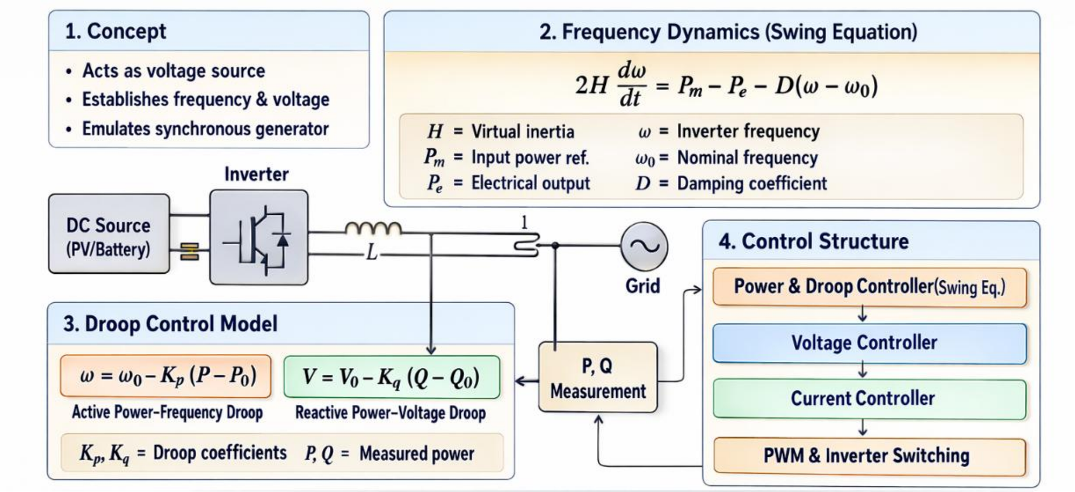

Fig. 3. GFM Base Model

3.4 Shortcomings of Traditional Virtual Inertia Methodologies

Even though virtual inertia control strategies have greatly enhanced the stability of the power systems that are dominated by inverters, various challenges remain to date. A lot of traditional methods rely on the solid inertia parameters and damping, which might not provide the most desirable results when the operating conditions or disturbances change. In real-life power systems, the operating environment is always changing through changes in load demand, renewable generation and network conditions [26].

The other weakness of the conventional approaches of virtual inertia is that they require true to life system models. Precise models may be hard to purchase in complicated and highly dynamic power systems where the renewable penetration level is high. This means that standard control strategies will fail to ensure the best performance under the conditions of the system that do not match the model [27].

Moreover, the alignment of multiple grid forming inverters presents other problems in terms of parameter tuning and stability. Poorly tuned virtual inertia parameters may initiate oscillation or violent system behavior, especially in large-scale distributed networks. These constraints explain why adaptive and intelligent control methods are required to dynamically change control parameters as system conditions evolve [28].

4 RL ALGORITHMS USED FOR GFM VIRTUAL INERTIA AND WHY

In grid-forming (GFM) virtual inertia control, the inverter is controlled so that it behaves similarly to a synchronous machine. Virtual reinforcement learning (RL) is applied to adjust online virtual inertia and damping rather than fixed values. The RL agent monitors grid stability indicators (frequency deviation, ROCOF, frequency oscillations), selects control variables including virtual inertia (J) and virtual damping (D), and is rewarded according to the level of improvement of frequency stability.

Most studies on GFM virtual inertia based on RL could be outlined as a Markov Decision Process (MDP):

$$M = (S, A, P, r, \gamma)$$

(S): state space (that the agent perceives)
(r): reward function (score)
(A): action space (what the agent varies)
(γ): discount (importance of the future)
(P): change of state (system dynamics)

Each time step, the RL agent measures grid/inverter signals (frequency error, ROCOF, power/voltage deviations), chooses control parameters (mainly virtual inertia and damping), and then gets a reward that is better when frequency is stable and oscillations are small. Safety limits are enforced by adding big penalties or stopping learning when constraints (frequency/current/saturation) are violated.

The control structure of RL-based virtual inertia adaptation in a grid-forming inverter is a closed-loop system as shown in Fig. 4. It demonstrates the utilization of measured grid variables by the RL policy in revising the VSG parameters in the overall control loop.

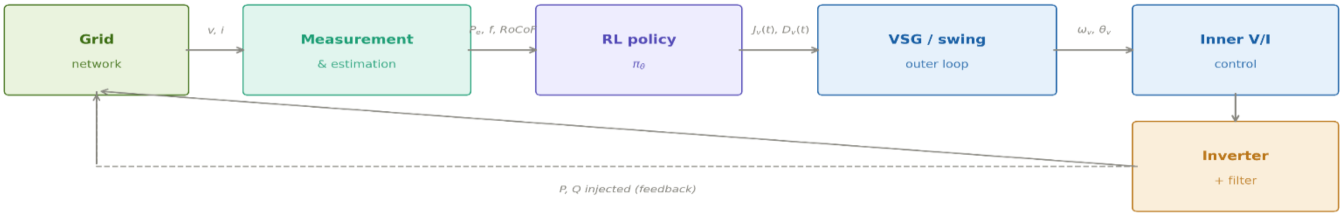

Fig. 4. Closed-Loop RL-Based VSG Parameter Adaptation in a Grid-Forming Inverter

4.1 Deep deterministic policy gradient family (DDPG, TD3)

To have continuous J, D actions (the virtual inertia and damping are real-valued, thus the controller should make smooth numbers, not steps).

- DDPG has seen extensive applications in VSG parameter tuning and is found in other related inverter control applications. It works because it can learn (with J and D online) a continuous control policy directly [29], [30], [31], [32].
- TD3 is a better variant of DDPG, which eliminates overestimation of critics, making learning and control more stable. It is clearly applied to the VSG parameter adaptation and confirmed in real-time simulation [33]. Also applied in virtual inertia control in microgrids [34] (not always, but algorithmically relevant is GFM).

4.2 Soft Actor-Critic (SAC)

SAC applies in cases of robustness where entropy regularization is favored, as it is usually effective in noisy settings, uncertainty about the parameters, and fluctuating conditions of the grid.

- Inertia - droop coordination Multi-agent SAC has been applied to inertia - droop coordination, where the actions of multiple inverters/controllers are required to coordinate [15].
- VSG single-agent SAC Single-agent SAC has been used to tune VSG inertia/damping tuning when the parameters of a single inverter are adjusted according to the frequency behavior [13].

4.3 Multi-agent procedures (MADDPG / Markov games)

They are employed in the case of several VSGs / several grid-forming units. When each unit tunes J, D individually, they will be able to interact to generate oscillations or inefficient power sharing. Multi-agent RL learns to coordinate.

- MADDPG has been applied in coordinated inertia/damping adaptation between multiple VSGs with centralized training and decentralized execution, which is feasible since training with complete system information may be done, whereas real-time control may be kept local [14].
- Distributed coordination has also been coordinated by multi-agent SAC, where in many cases it has superior robustness compared to entirely deterministic methods [15].

4.4 Discrete action policies and Q-learning

Used when actions are discrete (e.g., inertia may be able to alternate among a small number of levels only). This is not as flexible as the continuous tuning, but easier to implement.

- Q-learning of inertia and voltage control gain adjustment of the synchronverter [16].
- The damping of low-frequency oscillations by inertia tuning in Q-learning [35].
- WCDQN (a variant of DQN), when robust decision-making is needed, the discrete variety of VSG parameters in ship power systems is feasible [36].

4.5 ADP / value iteration / heuristic DP (control-theoretic RL)

They are dynamic programming / optimal control RL methods. Others apply them in place of deep RL as they are easily compatible with control theory and stability optimization.

- ADP-based optimal VSG control under uncertain grid conditions [37].
- ADP-based PQ-decoupling and oscillation reduction [38].
- Adaptive critic / heuristic DP for virtual-inertia-based inverter control [39], [40].

4.6 Comparative Summary of the Reviewed Literature

Table 2 is a summary of all grid-forming (GFM)-only reinforcement learning research of virtual inertia control based on the control interface presented in the literature. The table underlines what kind of method tunes each of the classes has, the most common RL algorithms used, and sample studies. The classification is beneficial in pointing out the key trends of current research, including direct virtual inertia and damping tuning, coordinated multi-device control, discrete adaptation, and physics-informed approaches.

Table 2 Core GFM-only RL virtual inertia papers by control interface

Interface (GFM)	What RL tunes	Typical RL algorithm	Representative refs
Direct J_v, D_v tuning	Virtual inertia & damping	TD3/SAC/DDPG	[12], [15], [29], [33]
Multi-device coordination	Inertia/damping and/or droop across units	MA-SAC / MADDPG	[14], [15]
Discrete adaptation	Stepwise inertia/gain changes	Q-learning / DQN variants	[16], [35]
Physics-embedded	Uses power-angle/rotor priors	Physics-embedded RL	[17]
Indirect inertia synthesis	Impedance/bandwidth shaping	DRL (various)	[15]
ADP / value iteration (GFM context)	Optimal VSG feedback control	ADP / VI	[37], [38]
“Accurate/effective inertia” focus	Equivalent inertia w/ damping coupling	DDPG-style	[41]
Identification enabling control	Inertia estimation rather than control	PPO-style	[42]

Table 2 indicates that the simplest method in GFM virtual inertia experiments is direct tuning of virtual inertia and damping coefficients (with continuous-action RL algorithms such as DDPG, TD3, and SAC often used). This is not surprising since inertia and damping are natural continuous control variables in VSG-based GFM systems. The other significant research direction is multi-device coordination, in which multi-agent algorithms, including MA-SAC and MADDPG, are applied to coordinate multiple units at once. In comparison, the Q-learning and DQN-based algorithms are more applicable when the inertia or control gains change not on a continuous basis but on a discrete one.

Fewer studies are about physics-embedded RL, indirect inertia synthesis, and ADP-based optimal control, indicating that the area is also shifting towards more structured and model-sensitive learning methods. Along with the choice of the algorithm, the modeling and validation methodology employed in each study has a significant impact on the believability and applicability of the obtained results. Table 3 provides a summary of model fidelities and validation methods commonly used in the GFM RL study of virtual inertia.

Table 3 Modeling and validation practice for GFM RL virtual inertia

Modeling fidelity	Typical Use	Representative refs
Swing-equation / reduced model	RL state/action design, conceptual analysis	[15], [17], [31], [43], [44]
State-space small-signal	Eigenvalue sensitivity, stability mechanisms	[44], [45], [46], [47], [48]
EMT (Simulink)	Training/validation under disturbances	[12], [13], [29], [32], [33], [49], [50]
Real-time / HIL	Feasibility and timing	[33], [42]

As Table 3 indicates, GFM RL virtual inertia research is usually built on a variety of levels of models. The models of reduced-order swing equations are commonly applied in the initial stage of design since they ease the state and action formulation and assist in clarifying the concept of control. The stability mechanisms and sensitivity of the eigenvalues are primarily studied with the help of state-space and small-signal models. In simulations of performance verification during disturbances and nonlinear operating conditions, electromagnetic transient (EMT) simulations, particularly in MATLAB/Simulink, are predominant. Nevertheless, few studies have gone further to real-time simulation or hardware-in-the-loop validation, meaning that most of the published research is at the level of simulation and not complete practical implementation.

In general, the literature reviewed indicates that the predominance of the continuous-action RL techniques in GFM virtual inertia control is justified by the fact that they are most appropriate in direct tuning of the inertia and damping parameters. Simultaneously, the practices of modeling and validation indicate that most of the studies remain focused on the simulation level, and the number of works that prove the feasibility in real time is lower. Hence, the improvement of the control algorithm itself and the enhancement of experimental validation and multi-device coordination in realistic grid conditions should be the focus of future research.

5 SYSTEM-LEVEL STABILITY IMPLICATIONS (GFM-FOCUSED)

5.1 Frequency nadir and RoCoF vs oscillatory modes.

- Increasing J_V (virtual inertia) tends to decrease RoCoF,
- Slow frequency response (system gets heavier to allow slow recovery)
- Interact with delays/filters,
- Reduce damping if D_V is not coordinated appropriately.
- It is stated in the literature that coordinated inertia damping tuning is necessary to prevent the exchange of RoCoF improvement by oscillations, just as it is necessary to coordinate multi-device coordination when multiple GFM/VSG units are operating simultaneously [12], [13], [14], [15], [41].

5.2 Small-signal stability and mode sensitivity

Virtual inertia has been observed to increase the likelihood of destabilization in the system when poor parameter choices are made, which in turn drives the design of a compensator and the choice of safe parameter space [12], [45], [48].

The time domain is frequently the only element of RS studied; fewer have established stability analysis by eigenvalue (small signal) analysis.

- The oscillations can be caused by parameter distributions between paralleled VSGs [15].
- Low-frequency oscillation damping using Q-learning directly controls oscillatory behavior [35].

5.3 Temporal stability of power-angle and fault behavior

Directly taken care of is transient stability (CCT, power-angle type behavior):

- Reinforcement learning based on transient stability enhancement and CCT analysis [51].
- Physics-based RL of transient power-angle stability in high VSG penetration environments [17].

5.4 Identification and effective inertia

One important arising concern is that the commanded Jv will not be equal to effective inertia because of converter control dynamics and measurement delay. This implies the same set of inertia may cause other responses to a system in practice. Inertia estimation Assistance with DRL [42] applies to work on inertia estimation of GFM converters because this area enables controllers to adjust according to the real inertia response rather than the desired value.

6 Discussion: What is Missing and What This Review Emphasizes

6.1 Stability Guarantees and Safe RL for GFM Virtual Inertia

The majority of RL-based GFM virtual inertia research primarily report enhanced time-domain performance, e.g. enhanced frequency response or less oscillation. Nevertheless, the aspects that require more attention are the following:

- Training monitoring of eigenvalues and damping ratio [38], [39], [40], [42], [46].
  Besides the findings in the form of waveforms, future research ought to confirm the fact whether the trained controller also enhances the small-signal stability properties. This assists in relating RL-driven tuning to known stability metrics of power-systems.
- Explicit constraint layers, e.g. QP-based safety filters [24].
  Safe RL is significant in GFM applications since unsafe control actions can have an impact on system stability. The constraint layers may be useful to make sure the learned policy does not go out of reasonable operating range.
- Swing-equation regularization Physics-informed regularization [4].
  Incorporation of physical knowledge into the training procedure can enhance the interpretability and reliability of the RL controller, as well as decrease the unphysical behavior of the control.
- Angular policy structures power aware [2].
  Because the relations involving power-angle are at the heart of GFM stability, the RL policies, where the linkage to these relations is explicitly considered, could offer more substantial and stronger control action.

6.2 Coordination at Scale

Even though the concept of multi-agent coordination has been proven in smaller systems [3], [14], scaling to large systems is still open. The following issues are important to wider GFM networks:

- Graph-structured policies
  They are more appropriate to large distributed systems because they can more effectively describe the interaction among several inverters all connected in a network.
- Delay and partial observability resistance.
  In real-life systems, there are always delays in communication and measurements that cannot be completed. The future RL coordination approaches must then be set to be not just effective in such non-ideal conditions.
- Sustained system-level goals.
  In larger systems explicitly stated global objectives, frequency nadir, RoCoF, and modal damping, are needed to ensure that every agent is working towards the same overall stability objective.

6.3 Effective Inertia and Observability

Another critical but difficult problem in inverter dominated systems is the estimation of effective inertia. The effectively determined inertia in GFM systems, unlike in synchronous machines, is affected by several control and network factors, thus it is hard to be directly determined.

- DRL estimation of inertia [32].
  Recent efforts indicate that DRL-based estimation of inertia can assist in the estimation-control systems. This has the potential to allow future controllers to estimate system inertia as well as to regulate virtual inertia settings in a closed loop.

7 CONCLUSION

The use of reinforcement learning to achieve virtual inertia adjustment in grid-forming inverters has become a viable approach to control in improving frequency stability of low-inertia power systems. The studied articles show that the continuous-action algorithms, including DDPG, TD3 and SAC, are very efficient in adapting the tuning of virtual inertia and damping coefficients when subjected to different grid perturbations. Multi-agent reinforcement learning methods are also used to enhance coordination between several units of inverters and physics-informed reinforcement learning adds more powerful connections between control behaviors and power-system dynamics.

Regardless of such developments, the bulk of published literature is restricted to validation by simulations, and fewer by hardware implementation or real-time execution. In addition, most reinforcement learning methods remain more concerned with time-domain performance measures, including frequency deviation, RoCoF, and settling time, whereas they give relatively less emphasis on classical measures of stability, including eigenvalue behavior, damping ratios and transient power-angle stability.

Future studies must thus focus on safe reinforcement learning, large scale inverter coordination, efficient inertia estimation and the more robust combination of classical stability analysis and adaptive learning-based control. The reliable implementation of reinforcement learning-supported virtual inertia in the power grids of the future that predominantly use renewable can only be achieved through such developments.

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