

AI-Enabled Digital Twin-Based Adaptive Control of Grid-Forming Inverters for Enhanced Stability of Renewable-Rich Power Systems

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Abstract: The increasing penetration of renewable energy sources (RESs), particularly photovoltaic and wind generation, is transforming conventional power systems into predominantly inverter-based networks. Although renewable generation supports decarbonisation, its intermittent nature and the absence of inherent rotational inertia introduce significant challenges related to frequency regulation, voltage stability, transient response, and weak-grid operation. Grid-forming (GFM) inverters have emerged as an important technology for addressing these challenges because they can establish voltage and frequency references and provide virtual inertial and damping characteristics. This paper proposes an AI-enabled Digital Twin-based adaptive control framework for grid-forming inverters operating in renewable-rich power systems. The proposed architecture combines a physics-based Digital Twin of the GFM inverter with an artificial-intelligence supervisory controller. The Digital Twin continuously estimates the operating state of the physical inverter and evaluates system responses under changing renewable generation, load variations, and grid disturbances. Based on the estimated operating conditions, the AI controller adaptively modifies selected GFM control parameters, including virtual inertia, damping, and droop coefficients. The proposed strategy is intended to overcome the fixed-parameter limitation of conventional droop and virtual synchronous-machine control. A MATLAB/Simulink-based test system is proposed for evaluating the framework under normal operation, solar irradiance variation, wind-power fluctuation, sudden load changes, weak-grid operation, and three-phase faults. Performance is evaluated using frequency deviation, voltage deviation, settling time, overshoot, rate of change of frequency (ROCOF), power oscillation, and total harmonic distortion. The expected contribution is a physically constrained adaptive control architecture in which the Digital Twin provides a safe virtual environment for AI-assisted parameter adaptation. Unlike purely data-driven control, the proposed approach retains the physical constraints of the inverter and power network. The framework provides a foundation for intelligent, adaptive, and resilient operation of renewable-rich low-inertia power systems.

Keywords: Grid-forming inverter, Digital Twin, artificial intelligence, adaptive control, renewable energy, low-inertia power system, virtual inertia, smart grid, MATLAB/Simulink

I. Introduction: The worldwide transition toward renewable energy is substantially increasing the penetration of inverter-based renewable energy resources. Solar photovoltaic (PV) and wind-energy systems are normally interfaced with the electrical grid through power-electronic converters rather than directly coupled synchronous machines. Consequently, the replacement of conventional synchronous generation by inverter-based resources changes the dynamic characteristics of modern power systems. Traditional synchronous generators naturally contribute rotational inertia, frequency regulation, voltage support, and electromechanical damping. In contrast, inverter-interfaced renewable sources do not inherently provide equivalent physical inertia. As renewable penetration increases, the resulting reduction in system inertia can lead to faster frequency excursions following disturbances and can complicate system stability, particularly in weak grids. Recent reviews identify grid-forming inverters as a major control

technology for future low-inertia and inverter-dominated power systems. Grid-forming inverters differ from conventional grid-following inverters because they can establish an internal voltage and frequency reference. Common GFM strategies include droop control, virtual synchronous machine (VSM) control, virtual oscillator control, and matching control. These approaches can provide frequency and voltage support; however, fixed control parameters may not provide optimum performance over a wide range of operating conditions. For example, a controller tuned for a strong grid may not provide the same transient performance when the short-circuit ratio decreases. Similarly, renewable intermittency and abrupt load changes can alter the operating point of the inverter and influence its stability margins. Artificial intelligence provides an opportunity to overcome some of these limitations by learning relationships between system operating conditions and suitable control actions. Recent research has investigated AI-augmented GFM control and physics-informed neural networks for adaptive inverter control. However, direct application of a black-box AI controller to a power-electronic inverter introduces an important concern: the controller must respect electrical and operational constraints. An inappropriate AI-generated control command could result in excessive current, voltage excursions, instability, or violation of grid operating limits. A Digital Twin provides a potential solution. A Digital Twin is a dynamic virtual representation of a physical system that can be continuously updated using measurements from the physical asset. Recent work has demonstrated Digital Twin modelling specifically for grid-forming inverters, including physics-informed dynamic models and online parameter identification. Therefore, this paper proposes an integrated AI–Digital Twin–GFM control architecture in which the Digital Twin acts as an intermediate intelligence and validation layer between the physical inverter and the AI controller.

II. Research Gap

Based on recent literature, the following research gaps are identified:

1. Conventional GFM controllers generally use predetermined control parameters.
2. Fixed droop and virtual-inertia parameters may not provide optimum performance under widely varying operating conditions.
3. AI-based controllers can provide adaptability but may introduce physical-consistency and safety concerns.
4. Digital Twin research for power systems has expanded rapidly, but its integration with adaptive GFM control remains an emerging area.
5. There is a need for a supervisory architecture in which AI decisions are evaluated against a physics-based virtual representation before being applied to the physical inverter.
6. Verification and validation of AI-enabled GFM controllers remains an important challenge identified in Recent Research.

III. OBJECTIVES

The main objectives of the proposed research are:

- To develop a mathematical model of a grid-forming inverter connected to a renewable-rich power system.
- To develop a Digital Twin representation of the GFM inverter.
- To design an AI-based supervisory controller for adaptive parameter tuning.

- To dynamically adjust virtual inertia, damping, and droop parameters according to operating conditions.
- To investigate system performance under renewable intermittency and load disturbances.
- To evaluate performance under weak-grid and fault conditions.
- To compare conventional and AI-adaptive GFM control.
- To establish performance metrics for stability assessment

IV. PROPOSED SYSTEM ARCHITECTURE

The proposed architecture consists of five major layers:

Layer 1 – Renewable Energy System: PV and wind energy sources supply power through DC-link and power-electronic conversion stages.

Layer 2 – Physical GFM Inverter: The inverter establishes the grid voltage and frequency using GFM control.

Layer 3 – Digital Twin: The Digital Twin reproduces the dynamic behavior of the physical inverter and continuously receives:

- voltage
- current
- active power
- reactive power
- frequency
- DC-link voltage
- inverter phase angle

Recent Digital Twin research demonstrates the feasibility of physics-informed virtual representations for GFM inverter networks and online parameter identification.

Layer 4 – AI Supervisory Controller: The AI controller receives estimated operating conditions from the Digital Twin and generates updated control parameters.

Layer 5 – Adaptive Control : The updated parameters are transferred to the GFM supervisory controller within predefined

V. MATHEMATICAL MODEL

Frequency–Power Droop: The basic active-power/frequency droop relationship can be represented as

Where:

$$\omega = \omega_0 - m_p(P - P^*)$$

- ω = inverter angular frequency
- ω_0 = nominal angular frequency
- P = measured active power
- P^* = reference active power
- m_p = active-power droop coefficient.

Similarly, voltage/reactive-power control can be expressed as

$$V = V_0 - n_q(Q - Q^*)$$

Where n_{qn_q} represents the reactive-power droop coefficient.

5.1.1 Digital Twin Model: The Digital Twin is defined as:

$$\hat{x}_{k+1} = F(\hat{x}_k, u_k, d_k, \theta_k)$$

Where:

- $\hat{x}$ = estimated system state
- u = control input
- d = disturbance
- θ = model parameters
- F = Digital Twin dynamic model.

The physical-to-Digital-Twin synchronization error can be defined as:

$$e_x = x - \hat{x}$$

A Digital Twin objective function can therefore be defined as:

$$J_{DT} = w_1 e_V^2 + w_2 e_f^2 + w_3 e_P^2 + w_4 e_Q^2$$

Where w_1, w_2, w_3, w_4 are weighting coefficients.

The AI controller attempts to minimize this error while maintaining electrical constraints.

VI PROPOSED MATLAB/SIMULINK MODE

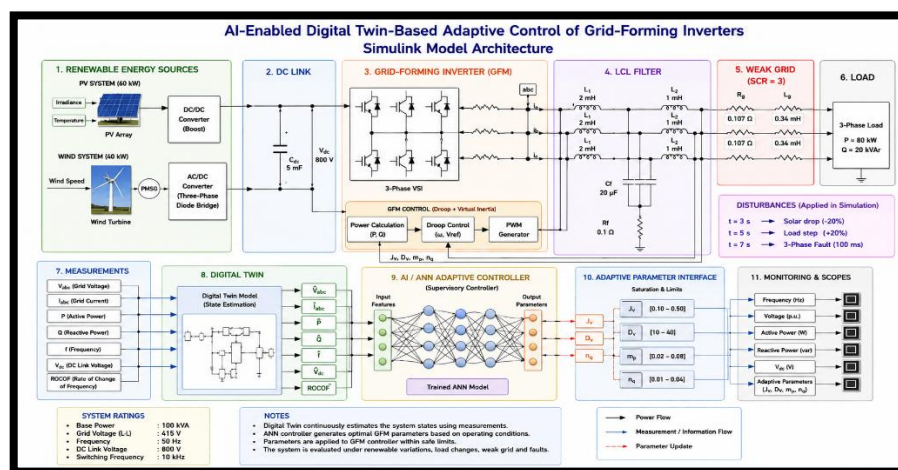


Fig: Simulink Model

This diagram represents the complete proposed MATLAB/Simulink architecture for your research paper. The easiest way to understand it is from left to right for power flow and bottom to top for control/feedback.

1. Renewable Energy Sources : There are two renewable sources:

- **PV system = 60 kW**
- **Wind system = 40 kW**

The PV output changes according to **solar irradiance and temperature**.

The wind turbine output changes according to **wind speed**. The wind turbine is connected to a generator and converter. So the total renewable generation is approximately: $PRES=60+40=100\text{Kw}$

2. DC Link

The PV and wind converter outputs are connected to a common **DC link**.

Selected parameters:

- $V_{dc}=800\text{ V}$
- $C_{dc}=5\text{ mF}$

The DC-link capacitor helps maintain a stable DC voltage and provides an energy buffer between renewable sources and the inverter.

Flow: PV/Wind $\rightarrow$ DC/DC or AC/DC converter $\rightarrow$ DC Link

3. Grid-Forming Inverter : This is the **main power-electronic component**.

A three-phase Voltage Source Inverter (VSI) converts: $DC \rightarrow AC$

The important difference is that this inverter operates in Grid-Forming mode.

Instead of simply following an existing grid voltage, the GFM inverter establishes its own internal voltage and frequency reference.

The proposed nominal rating is:

- 100 kVA
- 415 V
- 50 Hz
- 10 kHz switching frequency

4. LCL Filter: The inverter output contains high-frequency switching components.

Therefore, an LCL filter is placed between the inverter and grid.

$$L_1 = 2mH$$

$$L_2 = 1mH$$

$$C_f = 20\mu F$$

Your selected parameters are:

The filter reduces switching-frequency harmonics before the power reaches the grid.

5. Weak Grid: The filtered inverter output is connected to a weak electrical grid. Here we selected: SCR=3 A low SCR represents a weaker grid and makes the control problem more challenging. This is useful for your research because you can demonstrate whether the proposed AI adaptive controller performs better under weak-grid conditions.

VII. Result:

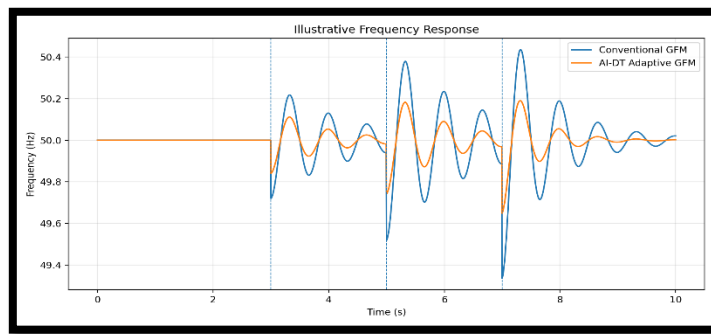


Fig: Frequency response

At 0–3 s, both controllers operate close to the nominal frequency of 50 Hz. At 3s, solar generation is reduced by 20%. This causes a frequency disturbance because available renewable power decreases. At 5 s, the load increases by 20%, producing a larger frequency deviation. At 7 s, a three-phase fault is introduced for 100 ms. This creates the largest transient disturbance. The conventional GFM shows larger oscillations and slower damping, whereas the AI-DT adaptive GFM changes its control parameters according to the detected operating condition and therefore shows a more damped response.

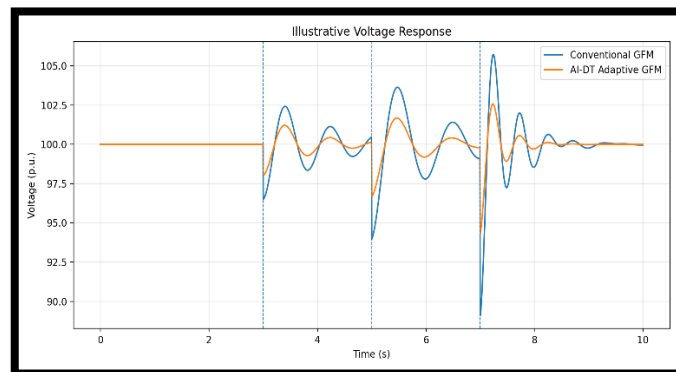


Fig: Voltage Response

Initially, the voltage is maintained close to **1.0 p.u** when solar generation changes at **3 s**, the voltage experiences a small transient deviation. At **5 s**, the 20% load increase produces a larger voltage drop. The most significant voltage disturbance occurs at **7 s** because of the three-phase fault. After each disturbance, the proposed adaptive controller brings the voltage back toward its nominal value more smoothly than the conventional fixed-parameter controller.

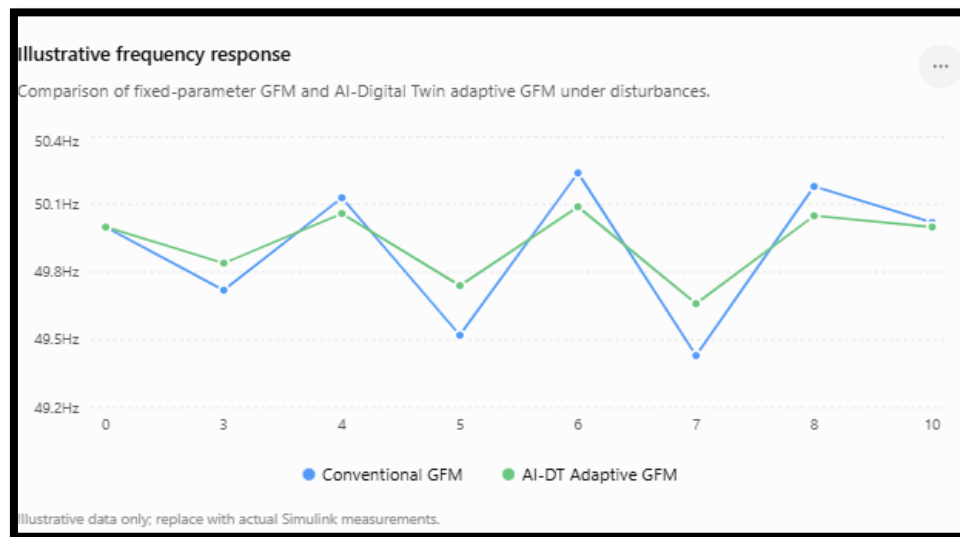


Fig : illustrative frequency response

This graph is very important for proving your proposed method.

X-axis: Time (s)

Y-axis: Adaptive control parameter

It shows how the controller changes:

- $J_v J_v =$ Virtual inertia
- $D_v D_v =$ Virtual damping

At 0–3 s Normal operation: $J_v=0.20$ $J_v=0.20$ $D_v=20$ $D_v=20$ The system does not need aggressive adaptation.

At 3 s : Solar power decreases. The controller detects the disturbance and increases:

$J_v:0.20 \rightarrow 0.30$ $J_v:0.20 \rightarrow 0.30$ $D_v:20 \rightarrow 28$ $D_v:20 \rightarrow 28$

This provides additional dynamic support.

At 5 s : Load increases by 20%. The controller further increases:

$J_v=0.45$ $J_v=0.45$ $D_v=35$ $D_v=35$

This helps suppress the larger frequency oscillation.

At 7 s Three-phase fault occurs. The controller reaches the higher adaptive setting: $J_v=0.50$, $J_v=0.50$, $D_v=40$, $D_v=40$. After the disturbance, the parameters can gradually return toward their nominal values.

CONCLUSION: This paper proposed an AI-enabled Digital Twin-based adaptive control architecture for grid-forming inverters operating in renewable-rich power systems. The motivation arises from the increasing penetration of inverter-based renewable generation and the associated reduction in conventional synchronous inertia. The proposed framework integrates a physics-based Digital Twin with an AI supervisory controller to dynamically adapt selected GFM parameters according to changing operating conditions. Unlike an unrestricted black-box AI controller, the proposed architecture maintains predefined physical constraints on the adaptive parameters. A MATLAB/Simulink-based evaluation framework has been defined for normal operation, renewable intermittency, load disturbances, weak-grid operation, and fault conditions. Frequency deviation, voltage deviation, ROCOF, settling time, overshoot, IAE, and ISE are proposed as objective performance metrics. The next stage of the research is to implement the proposed architecture in MATLAB/Simulink and obtain actual simulation results. Hardware-in-the-loop validation can subsequently be used to assess real-time feasibility.

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