Improving voltage stability in isolated renewable energy microgrids using virtual synchronous generators

Ahmad Supawi Osman, Aidil Azwin Zainul Abidin
College of Engineering, Putrajaya Campus, Universiti of Tenaga Nasional, Selangor, Malaysia

Article Info	ABSTRACT
	The integration of renewable energy systems (RES) and distributed generation (DG) into microgrids introduces significant challenges in maintaining voltage stability due to intermittent generation and reduced rotational inertia. This systematic review critically examines advanced control strategies aimed at enhancing voltage resilience in isolated RES-driven microgrids. Particular focus is placed on virtual synchronous generators (VSGs), which emulate electromechanical dynamics of synchronous machines via state-space modeling, and model predictive control (MPC), which enables real-time control optimization under multi-constraint scenarios. The review synthesizes literature on coupling–decoupling behavior, impedance sensitivity, and dynamic voltage response under varying load conditions. Additionally, it evaluates the role of hardware-in-the-loop (HIL) platforms and Runge-Kutta-based simulations in validating control models for real-time deployment. A structured framework is proposed, aligning VSG-based inertia emulation with predictive control to address voltage dips, oscillations, and transient instabilities. The findings highlight both theoretical gaps and implementation opportunities for achieving robust voltage stabilization in next-generation microgrids. *This is an open access article under the CC BY-SA license.*

Corresponding Author:

Ahmad Supawi Osman
College of Engineering, Putrajaya Campus, Universiti of Tenaga Nasional
Selangor, Malaysia
Email: ahmadsupawi@yahoo.com

1. INTRODUCTION

The global energy landscape is rapidly transitioning toward sustainability in response to the urgent need to reduce greenhouse gas emissions and mitigate climate change. Central to this transformation is the integration of renewable energy sources (RES), such as solar and wind, into existing power systems. Unlike conventional energy generation, RES is inherently decentralized and variable, introducing new layers of complexity in ensuring grid reliability. In this regard, challenges such as voltage regulation, fault response, and transient stability have become more pronounced, particularly in isolated or weak-grid environments [1].

Notably, the unpredictable nature of RES generation disrupts the predictable flow of traditional centralized grids, where supply and demand were once stable and controllable [2], [3]. Today's evolving power infrastructure must contend with both intermittency and rising consumption, demanding smarter, more adaptive system modeling approaches [4]. To address these challenges, real-time simulation (RTS) has emerged as a powerful tool for evaluating system behavior under dynamic operating conditions.

RTS platforms leverage multi-processor computing to simulate power system behavior in real time, mirroring physical conditions without the risks or limitations of field testing. This enables non-destructive testing (NDT) of operational systems, offering invaluable insight into voltage behavior, fault propagation, and the real-time effectiveness of control and protection strategies [5]. Within this context, this review examines the synergistic

role of state-space modeling and RTS in enhancing the understanding of transient phenomena and supporting the development of resilient grid architectures. The ability to simulate and analyze these complex interactions is essential for future-proofing power systems and ensuring stability in the age of renewable energy.

− Contextual background

In recent decades, the growing reliance on simulation and NDT has become vital for evaluating complex engineering systems, particularly in power delivery networks facing increasing operational variability. This review presents a framework for addressing challenges inherent in bus networks and voltage control, especially under the evolving conditions introduced by RES. Numerical simulation techniques provide engineers with the ability to predict voltage and current behavior across nodes and branches with high precision, independent of physical topology or environmental constraints.

Traditional steady-state simulations typically rely on root-finding algorithms, such as the Newton-Raphson method, which are well-suited for solving nonlinear equations at system equilibrium. By contrast, dynamic simulations capture instantaneous and fluctuating behavior in variables such as voltage, current, and generator rotor speed. These simulations often require solving first-order differential equations to reflect time-dependent irregularities in system performance. Among the numerical integration techniques, the Runge-Kutta method is frequently employed to compute dynamic states with enhanced temporal accuracy.

The increasing penetration of RES into national grids has further complicated this landscape, exposing the limitations of conventional simulation tools. These tools often fall short in modeling transient events, rapid fluctuations, and fault-driven instability with sufficient resolution [6]. The stochastic nature of RES generation introduces voltage variability, weakens traditional protection schemes, and alters system inertia, all of which complicate stability assessments [7].

In this regard, RTS has emerged as a transformative tool for analyzing power systems under dynamic operating conditions [8]. RTS enables real-time modeling that aligns simulation outputs with physical time, thereby offering clearer insights into transient phenomena, particularly those arising in RES-integrated networks [9]. This is especially crucial in modern grids, where high levels of distributed generation may trigger sudden voltage deviations, conditions that traditional simulators often fail to predict or mitigate effectively [10].

− Problem statement

Recent advancements in numerical modeling have demonstrated that optimized state-space formulations and improved derivative approximations can significantly enhance real-time computational efficiency and accuracy in dynamic system simulations [11]. These developments complement traditional numerical approaches that remain central to electrical power system analysis, whether through commercial software or custom-coded platforms, for studying bus networks under diverse operating conditions [12]. Dynamic simulations are particularly valuable for capturing instantaneous variations in voltage, current, and rotor speed [13]. However, their accuracy still depends on discretization methods that approximate continuous-time derivatives over finite time steps. Smaller time steps increase precision but raise computational cost, whereas larger steps improve efficiency at the expense of fidelity. This trade-off becomes critical in real-time environments where each second of system activity must be computed within the same second. Although advanced solvers such as the Runge–Kutta family reduce these errors, their sequential computation limits performance when modeling fast transients or high-frequency switching events. Their accuracy often relies on numerical solvers such as the Runge-Kutta family, which extend the finite-difference derivative approximation:

$$\frac{dx(t)}{dt} = \lim_{\delta t \to 0} \frac{x(t+\delta t) - x(t)}{\delta t} \tag{1}$$

In digital environments, this time step is finite rather than infinitesimal, creating a trade-off: smaller intervals yield accuracy but demand more computation, while larger ones improve speed at the cost of fidelity. Real-time contexts make this balance critical when simulating fast transients or high-frequency switching events. Runge-Kutta methods mitigate the trade-off by incorporating intermediate derivative evaluations, enabling precise tracking of system dynamics without impractically small steps.

Building on this foundation, state-space modeling provides a matrix-based framework to simulate transient phenomena with greater accuracy, especially in grids with high renewable energy source (RES) penetration. Such environments face challenges, including voltage instability, bidirectional flows, and altered protection coordination. Solar PV integration, in particular, introduces voltage rise, reverse power flow, and heightened fault levels conditions that traditional steady-state methods struggle to address. Integrating state-space approaches with RTS enables improved prediction and management of these dynamic behaviors. In this regard, principles from advanced discrete-time control theory emphasize that digital-domain implementations must address sampling, delay, and gain-adjustment effects to preserve system stability and precision [14].

Unlike offline simulations, real-time simulation requires each second of system activity to be computed within the same second, a challenge magnified in large-scale systems where computational demand

grows exponentially. Conventional simulators often fail to meet this requirement, limiting their ability to capture transient dynamics in RES-heavy microgrids [15]. Building on these foundations, state-space modeling provides a matrix-based framework capable of representing transient phenomena with greater precision, particularly in grids with high-RES penetration. Such systems face persistent challenges of voltage instability, bidirectional power flow, and protection coordination, which traditional steady-state methods cannot adequately capture. This underscores the need for advanced, state-space-based real-time simulation frameworks that combine the accuracy of modern numerical algorithms with the computational efficiency required for ensuring voltage stability in distributed renewable grids.

− Objectives

Real-time simulation imposes a unique computational demand: system events must be modeled within the same time window in which they occur. A one-second transient, for instance, must be processed in precisely one second. This requirement becomes particularly challenging in modern grids with high-RES penetration, where single-processor systems often buckle under the heavy computational load [16]. Parallel processing offers a partial remedy by distributing tasks across multiple processors to reduce latency and boost throughput [17]. Yet, true real-time fidelity requires more than speed; it demands seamless interaction with external devices such as relays, electrical machines, and protection units, where human and hardware responses are also part of the loop [18], [19].

Within this context, hardware-in-the-loop (HIL) and power hardware-in-the-loop (PHIL) methods have become essential. By embedding physical components into the simulation loop through standardized protocols, they create closed-loop environments that accurately reflect operational dynamics [20]. This study employs an OPAL-RT platform integrated with MATLAB/Simulink and RT-LAB to model a microgrid incorporating photovoltaic generation, synchronous machine behavior, and bus interconnections, enabling real-time prototyping and validation [21].

The objectives of this review are fourfold. First, to investigate the transient behavior of RES-integrated systems during faults, with emphasis on voltage stability, fault duration, and mitigation. Second, to assess advanced control and protection strategies using real-time simulation for validation. Third, to propose an improved framework that merges state-space modeling with parallel processing for higher efficiency and fidelity. Finally, to evaluate HIL testing as a bridge between simulation and real-world application. Collectively, these aims position real-time, model-driven simulation as a tool not only for safeguarding voltage stability and reducing outages but also for optimizing performance under fluctuating generation and demand [22], [23]. As renewable integration accelerates, such approaches will be vital for informing present practice and shaping future-ready grid infrastructures [24].

2. METHOD

This study adopts a structured methodological framework to investigate dynamic simulation approaches for modeling power systems with high penetration of RES. The objective is to optimize system operation, improve energy interaction between components, and develop practical strategies for enhancing voltage stability. As illustrated in Figure 1, the methodology progresses through three stages: preliminary, implementation, and result.

In the preliminary stage, system configuration and data collection establish foundational parameters using specification data. The implementation stage follows with component model development, system integration, and validation, supported by real operating data to ensure fidelity. Finally, the result stage encompasses scenario simulation and the development of effective operational strategies, verified through validated datasets. This staged progression ensures simulations evolve from abstract models to real-world relevance, enabling iterative refinement of system performance.

To contextualize this approach, it is important to note the difference between dynamic and static simulations. Dynamic simulations provide complex, accurate insights but are time-consuming and less effective at identifying failure boundaries, whereas static simulations are quicker, simpler, and better at indicating approximate limits [25]. This comparison reinforces why dynamic approaches, though resource-intensive, are better suited for capturing the transient behaviors central to RES-integrated systems [25].

2.1. State-space model

The state-space model provides a robust mathematical framework for describing dynamic system behavior, particularly valuable in modern control applications with renewable energy sources (RES) [25]. By expressing system dynamics through first-order differential equations, it captures the continuous evolution of internal states under varying inputs and feedback, making it well-suited for real-time simulations. Higher-order differential systems can also be simplified into first-order forms, improving computational efficiency and enabling controller design [26]. The general continuous-time linear time-invariant (LTI) state-space representation is:

$$x(t) = Ax(t) + Bu(t)$$
$$y(t) = Cx(t) + Du(t) \qquad\qquad (2)$$

Where: $x(t)$ is the state vector, representing internal system states, $u(t)$ is the input vector, representing external driving signals, $y(t)$ is the output vectors, containing the measurable outputs, A, B, C and D matrices describe system dynamics, input effects, output mappings, and direct transmission paths, respectively.

These relationships are clearly illustrated in Figure 2, which provides a structural view of how the state-space components interconnect. The input $u(t)$ influences the system both directly through matrix D and indirectly via the state evolution path, where it combines with current state values $x(t)$ through matrices A and B. The resulting state updates are then processed by matrix C to yield the output $y(t)$. The integrator block $\frac{1}{s}$ captures the continuous accumulation of system dynamics over time.
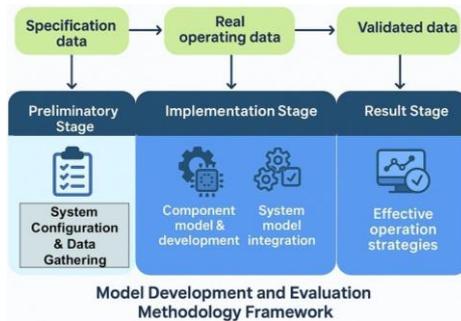

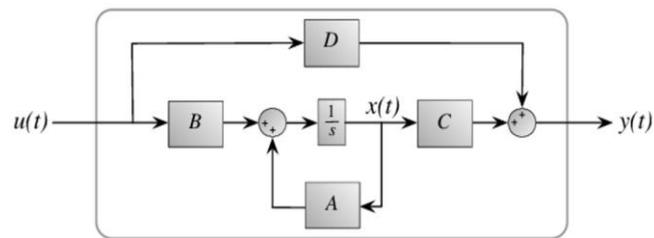Figure 1. Model development and evaluation methodology framework

Figure 2. State-space block diagram structure

In real-time applications such as HIL testing, state-space models must remain synchronized with real-time clocks to ensure accurate controller interaction [27], [28]. To achieve this precision, field programmable gate arrays (FPGAs) are increasingly employed for their parallel processing speed and ultra-low latency. Embedding models directly in FPGA logic enables sub-microsecond resolution, allowing detailed simulation of electromechanical dynamics critical for microgrids and power electronics [29]. Hybrid HIL setups, where part of the system is physically realized and the rest simulated, further allow safe testing of control algorithms under conditions such as frequency deviations or grid faults.

The advantages of FPGA-enhanced state-space simulations include nano second-level accuracy, parallel computation for speed, reprogrammability for diverse scenarios, and scalability for complex architectures [30]. These features make them indispensable for renewable-integrated grids where adaptability and precision are paramount [31]–[33]. To align continuous models with digital processors, state-space equations are typically discretized using methods like Euler or Runge–Kutta, ensuring updates match real-time sampling frequencies. Once deployed on FPGA platforms or digital signal processors, these models enable high-fidelity emulation of voltage and current fluctuations, as well as live interaction with analog/digital I/O.

Recent applications highlight their relevance: state-space estimators embedded in real-time simulators have improved phase tracking and voltage profile regulation, while FPGA-based fractional-order emulations with analog interfaces have demonstrated effective operation in voltage-sensitive environments. Collectively, real-time implementation of state-space models strengthens both the accuracy of transient analysis and the deployability of advanced voltage control strategies in isolated or weakly coupled microgrids.

2.1. Mathematical model in digital simulator

This section delves into the implementation of mathematical modelling methods, particularly the Runge-Kutta and state-space techniques, for simulating dynamic systems in digital environments. These methods are essential for translating continuous-time behaviors into discrete-time formats suitable for digital computation. The Runge-Kutta method, for instance, is widely recognized for its ability to generate accurate approximations of instantaneous state values derived from first-order differential equations. When higher-order equations are involved, they are typically decomposed into an equivalent set of first-order equations prior to discretization.

To simulate these systems in digital platforms such as MATLAB/Simulink, the original continuous-time differential equations must first be transformed into discrete equivalents. This step is crucial for compatibility with digital solvers, which operate on a finite time step, denoted as δt. A representative example can be found in the classic RLC circuit, which consists of a resistor (R), inductor (L), and capacitor (C) arranged in series [34].

The RLC circuit serves as an ideal candidate to illustrate the state-space framework due to its simplicity and well-defined dynamic behavior. In this setup, the capacitor voltage and inductor current are typically chosen as the state variables. The system's governing equations are derived from Kirchhoff's Voltage and Current Laws, and then reformulated into a state-space structure to simplify computational analysis. The dynamic behavior is first expressed through the following differential equations:

$$L \frac{di_L(t)}{dt} = V_s(t) - R * i_L(t) - v_c(t)$$
$$C \frac{dv_c(t)}{dt} = i_L(t) \tag{3}$$

Where: L represents the inductor, C represents the capacitor, $v_c(t)$ represents the voltage across the capacitor (state variable), $i_L(t)$ represents the current state of the inductor (state variable), and $V_s(t)$) represents the source input voltage. To facilitate digital simulation, these equations are represented in matrix form as (4).

$$\begin{bmatrix} \frac{dv_C(t)}{dt} \\ \frac{di_L(t)}{dt} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{C} \\ -\frac{1}{L} & -\frac{R}{L} \end{bmatrix} \begin{bmatrix} v_c(t) \\ i_L(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{L} \end{bmatrix} V_s(t) \tag{4}$$

This continuous-time model can then be discretized by applying the definition of the derivative using a finite time step, T_S. Afterwards, using the definition given in (1) and replacing it in (4) for every derivative, the relations in (5).

$$\begin{bmatrix} \frac{v_C(t+T_S)-v_C(t)}{T_S} \\ \frac{i_L(t+T_S)-i_L(t)}{T_S} \end{bmatrix} = \begin{bmatrix} 0 & \frac{1}{C} \\ -\frac{1}{L} & -\frac{R}{L} \end{bmatrix} \begin{bmatrix} v_c(t) \\ i_L(t) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{L} \end{bmatrix} v_s(t) \tag{5}$$

Using the discrete time variable $t = kT_s$, we can reformulate the equations as (6).

$$\begin{bmatrix} v_c(k+1) \\ i_L(k+1) \end{bmatrix} = \begin{bmatrix} 1 & \frac{T_S}{C} \\ -\frac{T_S}{L} & -R*\frac{T_S}{L}+1 \end{bmatrix} \begin{bmatrix} v_c(k) \\ i_L(k) \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{T_S}{L} \end{bmatrix} v_s(k) \tag{6}$$

In compact form (6) can be expressed in (7).

$$\vec{x}(k+1) = G\vec{x}(k) + H\vec{u}(k) \tag{7}$$

Given that the system is given a set of initial state values designated as $\vec{x}(0)$ the values of the states can be stated as in (8). This derivation was previously done in [13], [14].

$$\vec{x}(k) = G^k \vec{x}(0) + \sum_{i=0}^{k-1} G^i Hu(k-1-i) \tag{8}$$

The matrix G^k is defined as the state transition matrix which maps the initial values of the states and inputs of the system to the system state present values. In a digital simulation, the state transition matrix is used to predict future states from the initial states. In the case presented in Figure 3, the system is a linear time-invariant (LTI) system. For systems that are linear but time-varying, the relation in (8) needs to be changed to (9).

$$\vec{x}(k) = \prod_{i=0}^{k} G(i)\vec{x}(0) + \sum_{i=0}^{k-1} \sum_{j=0}^{i} G(j)Hu(k-1-i) \tag{9}$$

To validate this discretized model in simulation, a test case was constructed by assigning initial conditions: the capacitor voltage was set to 100 V, the inductor current to 1 A, and the source voltage to 0 V (isolating the initial response only). The resulting state evolution simplifies to (10).

$$\vec{x}(k) = \prod_{i=0}^{k} G(i)\vec{x}(0) \tag{10}$$

Since the sampling time was set to $0.1 \, ms$, it would, therefore, take 200,000 samples for the response of 20 seconds to be obtained. In each iteration, the instantaneous state will be calculated using (11). The simulated response is often the accuracy of the discretized model, clearly capturing the transient oscillations and settling behavior inherent to the RLC circuit under the specified initial conditions.

$$c_{ij} = \sum_{k=1}^{m} a_{ik} b_{kj} \tag{11}$$

2.2. State-space models and advanced control techniques

State-space models underpin many advanced control strategies for microgrid voltage regulation, especially under intermittent renewable inputs. By estimating key system states, such as inverter terminal voltages and currents, they enable real-time feedback and predictive adjustments, forming the backbone of robust and adaptive controllers [35].

As shown in Figure 3, mixed H∞ and passivity-based design integrates GPS synchronization and virtual impedance shaping to achieve decentralized voltage and frequency regulation, even when communication links are weak [36]. A simpler option is the single-loop state feedback design in Figure 4, which reduces sensor requirements while maintaining accurate voltage tracking, well-suited for embedded microgrid applications [36].
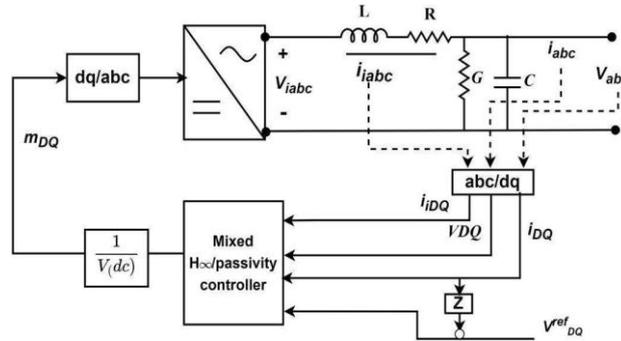

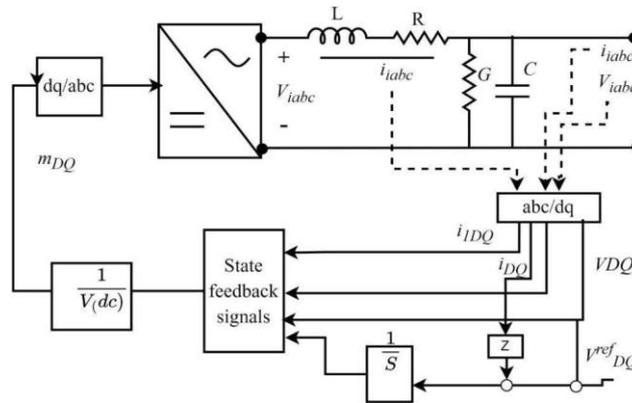Figure 3. Mixed H infinity and passivity control design [36]

Figure 4. Single loop state feedback design [36]

Back-stepping techniques extend this toolbox by applying recursive Lyapunov tuning to stabilize DC-link voltage and power flow at the PCC (Figure 5). Adaptive observers and reference-signal generation, illustrated in Figure 6, further enhance resilience by estimating system states in real time and correcting voltage deviations during load shocks or variable renewable input [37], [38]. As shown, the renewable source extractor and associated power-electronic converter ensure maximum power point tracking of the solar- or wind-based source, while a DC-link capacitor and single-phase full-bridge inverter feed the AC bus through an LC filter. The measured voltage and current signals are processed by a state observer that reconstructs unmeasured states and an adaptive reference module that updates the control targets. These outputs drive the back-stepping controller, which generates the pulse width modulation (PWM) control signals for inverter switches S_1–S_4, thereby maintaining voltage stability under fluctuating load and generation conditions. Across these strategies, state-space models remain the structural core that links system dynamics to advanced controllers. Whether through robust H∞ design, simplified state feedback, or adaptive back-stepping, their integration ensures responsive and sustainable voltage stability in modern renewable-integrated microgrids.
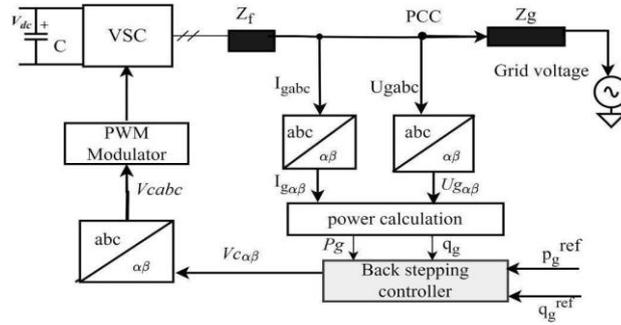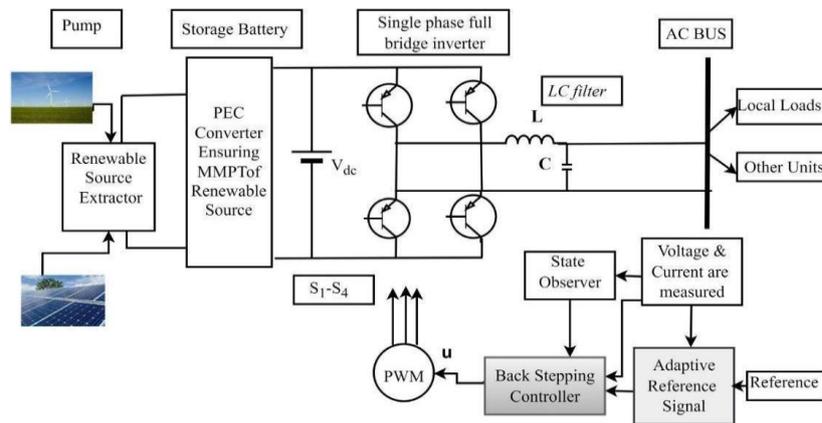
Figure 5. Back-stepping control technique [37]

Figure 6. Adaptive reference signal and state observer with working of back-stepping in microgrid [38]

3. REAL-TIME DIGITAL SIMULATOR

Real-time digital simulation represents a key advancement in system analysis, enabling models to run in strict synchrony with actual clock time. Each computational step must be completed within the predefined interval; otherwise, an overrun occurs, degrading accuracy or halting the simulation [39]. To manage this, platforms range from accessible tools like Simulink desktop real-time (SDRT) to advanced utility-scale systems such as RTDS and OPAL-RT, the latter noted for its parallel-processing architecture and high-fidelity performance [40], [41].

A central feature of this paradigm is HIL testing, which links digital simulations with real hardware via communication protocols (Ethernet, serial, parallel). This setup allows controllers, relays, and inverters to interact with simulated grid conditions in real time, offering a safe, cost-effective means of validating devices under extreme or faulted scenarios [42], [43]. For instance, protective relay responses can be tested using SDRT linked via Ethernet without needing physical field hardware, accelerating prototyping and reducing development risks.

Among available platforms, OPAL-RT stands out for its ability to distribute tasks across multi-core processors and integrate seamlessly with RT-LAB and MATLAB Simulink. This environment supports intuitive model development, rapid validation, and dynamic parameter tuning. Moreover, OPAL-RT's compatibility with FPGAs enhances speed, accuracy, and flexibility by embedding state-space models directly into customizable hardware logic [44], [45].

As shown in Figure 7, OPAL-RT setups integrate controllers at multiple levels (primary, secondary, tertiary) with energy sources, relays, and storage devices connected through AC/DC buses and communication channels [46]. This configuration provides a comprehensive real-time environment where hardware and software co-exist, enabling engineers to evaluate microgrid behavior under a variety of operating conditions.

3.1. Matrix multiplication algorithm or iterative algorithm

When applying the classical definition of matrix multiplication directly, the resulting algorithm involves a computational time complexity of $O(n^3)$, requiring approximately n^3 field operations to multiply two $n \times n \times n$ matrices [47]. Specifically, if $C=AB$, where A is an $n \times m$ matrix and B is an $m \times p$ matrix, from this, a simple

algorithm can be constructed which loops over the indices i from 1 through n and j from 1 through p, computing the above using a nested loop, then the resulting matrix C of size $n \times p$ is defined element-wise as (11).

Matrix operations form the computational backbone of real-time simulators. In RTS environments, these operations must be completed within strict time constraints, as overruns compromise both accuracy and simulation stability [47]. Algorithms are therefore optimized for parallel execution, ensuring large system matrices, common in renewable-integrated grids, can be solved rapidly. Approaches such as block-partitioning and sparse matrix optimization reduce computational burden, while real-time solvers are further accelerated through hardware support like FPGAs and graphics processing unit (GPU) cores [48].

These advances allow RTS platforms to capture fast transients in microgrids, such as those caused by inverter switching or sudden renewable fluctuations, without sacrificing numerical precision. Importantly, the balance between accuracy and computational efficiency remains a defining trade-off: finer resolution improves fidelity but increases processing demand, highlighting the importance of optimized algorithms for scalable renewable applications [49].
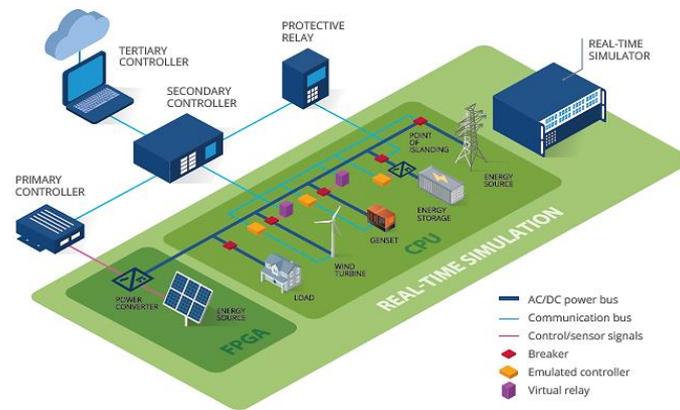

Figure 7. Real-time digital simulation setup using OPAL-RT system [46]

3.2. Divide-and-conquer algorithm

An alternative to the iterative algorithm is the divide-and-conquer algorithm for matrix multiplication. This relies on the block partitioning, which works for all square matrices whose dimensions are powers of two, i.e., the shapes are $2^n \times 2^n$ for some n. The matrix product is now the block partitioning is expressed as (12).

$$C = \begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix}, A = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}, B = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \tag{12}$$

The resulting matrix multiplication becomes (13).

$$\begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} = \begin{bmatrix} A_{11}B_{11} + A_{12}B_{21} & A_{11}B_{12} + A_{12}B_{22} \\ A_{21}B_{11} + A_{22}B_{21} & A_{21}B_{12} + A_{22}B_{22} \end{bmatrix} \tag{13}$$

This approach requires eight recursive multiplications of submatrices, followed by summation of the resulting matrix blocks. The computational complexity of the divide-and-conquer method is characterized by the recurrence. The complexity of this algorithm as a function of n is given by the recurrence.

$$T(1) = \theta 1 \tag{14}$$

$$T(n) = 8T\left(\frac{n}{2}\right) + \theta(n^2) \tag{15}$$

Accounting for the eight recursive calls on matrices of size $\frac{n}{2}$ and $\theta(n^2)$ to sum the four pairs of resulting matrices element-wise. Application of the master theorem for divide-and-conquer recurrences shows this recursion to have the solution $\theta(n^3)$, the same as the iterative algorithm.

To manage system complexity, divide-and-conquer strategies decompose large power-system models into smaller subsystems, solved independently before results are recombined [50]. This modularity enables efficient use of parallel processors, reducing latency and allowing real-time analysis of high-dimensional grids. Within microgrid studies, such decomposition supports flexible modeling of diverse components, PV arrays,

wind turbines, and energy storage, while ensuring interactions at the system boundary remain accurate [51]. Applied in RTS, this approach enhances both scalability and adaptability. Researchers can isolate critical subsystems (e.g., converters or faulted lines) for detailed analysis while retaining a simplified model for the rest of the network. This layered fidelity ensures that computational resources are directed toward the most dynamic or vulnerable sections, improving both speed and insight [52].

3.3. Renewable electricity integration

Integrating renewable energy into power networks challenges traditional simulation paradigms due to intermittency, reduced inertia, and bidirectional power flows [53]. RTS platforms address these by enabling real-time emulation of renewable generators, inverter dynamics, and grid interactions under variable conditions [54]. Unlike offline simulations, which often fail to capture abrupt transitions, real-time models replicate voltage dips, frequency swings, and harmonic distortion with millisecond accuracy.

This fidelity is crucial for validating advanced control strategies, such as virtual inertia injection and adaptive voltage regulation, under realistic renewable fluctuations. Moreover, the coupling of RTS with HIL testing allows physical controllers and relays to be evaluated under simulated disturbances, ensuring that strategies tested in the lab translate effectively to real systems [55]. As renewable penetration continues to rise, real-time integration studies provide operators with predictive insights to safeguard grid stability while advancing toward low-carbon energy targets [56].

The structural transformation illustrated in Figure 8 underpins the growing complexity of the grid. Whereas the conventional model featured a centralized control hierarchy, the modern system is increasingly meshed and amorphous, populated by generators with varying control logic and feed-in behaviors. Today's grid integration strategies often rely on voltage-controlled inverters using subharmonic or space-vector modulation. These inverters aim to locally stabilize the grid by supplying the necessary active and reactive power based on real-time grid conditions. However, a key limitation lies in their dissimilarity to synchronous machines, the very systems on which historical grid stability has been built [48].

To preserve the grid's essential properties, such as automatic balancing across areas and predictable dynamic behavior, it is therefore critical to develop inverter-based systems that replicate the functional identity of synchronous generators. This involves more than just control strategy refinement; it requires a systemic rethinking of how inverters interface with both energy sources and the grid. The goal is to create a seamless integration where inverters act not as isolated controllers, but as grid-participating entities with inertia, droop characteristics, and fault ride-through behavior comparable to electromechanical systems.
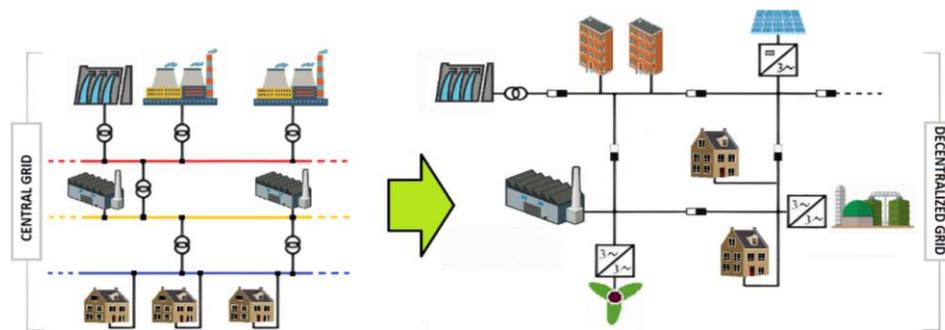

Figure 8. Change in the structure of generation and distribution of electrical energy [48]

4. REAL-TIME SIMULATION

Simulation creates mathematical models to replicate real-world system behavior. This paper focuses on fixed-step discrete-time simulations, widely used in real-time applications for their predictability and consistent update intervals, unlike variable-step methods that are unsuitable for real-time operation [50]. In such environments, each state is updated using equations solved at every time step. The challenge lies in computing all updates within the allotted interval: if faster, it is an accelerated simulation; if slower, it becomes an offline simulation.

Real-time simulation, however, demands strict synchronization with wall-clock time. For instance, a 1 ms system step requires all calculations and any hardware interactions to complete within that same 1 ms. Finishing early results in idle waiting, while overruns cause the simulation to lose fidelity [48]. A valid real-time simulator, therefore, requires both computational accuracy and timing compliance, providing a credible digital twin for hardware-in-the-loop testing, control validation, and fault emulation [49].

4.1. Power generation application

Real-time simulation plays a central role in validating power generation and control systems, including high voltage direct current (HVDC) links, flexible alternating current transmission systems (FACTS) devices, STATCOMs, and protection systems. Before deployment, controllers undergo thousands of deterministic and randomized test cases in HIL environments to ensure resilience under diverse faults and interactions with other devices [50]. Protection validation further benefits from real-time testing. While offline tools such as the alternative transient program (ATP) and electromagnetic transients' program (EMTP) aid early development, only real-time setups can replicate bidirectional interactions between protective relays and the grid. This allows closed-loop evaluation of relay responses across varying conditions, reducing the risk of mis-coordination or cascading failures.

As distributed generation (DG) and RES penetration grows, converters introduce fast-switching dynamics that coexist with slower electromechanical responses from synchronous machines. Simulating such hybrid systems is computationally demanding, especially at large scales. Offline studies often prove too slow, whereas real-time simulation enables agile scenario-based assessments, identifying worst-case events and informing proactive grid planning [51].

4.2. Renewable energy implemented state-space models

State-space modelling provides a robust framework for managing RES dynamics by translating multi-variable systems into structured equations. Unlike classical models, modern state-space frameworks capture nonlinearities inherent in photovoltaics, batteries, and wind turbines, enabling accurate predictions under variable conditions. They also integrate technical and economic parameters, offering decision-making tools for distributed energy management [51].

A key advancement is the integration of model predictive control (MPC). Operating on a predictive basis, MPC anticipates disturbances and adjusts responses in real time, while adhering to operational constraints [54], [55]. Event-based MPC further refines this by intervening only during significant deviations, reducing control actions by up to 65%, which minimizes component stress, lowers maintenance costs, and extends battery life [56], [57]. Beyond reliability, this approach improves energy scheduling, reduces grid dependency during peak demand, and supports decarbonization by limiting reliance on fossil peakers. Together, state-space modelling and predictive control provide a scalable pathway toward smart, flexible, and sustainable renewable energy systems [58].

4.3. Event-based control architecture

Event-based control has gained traction as a solution to the computational burden of continuous control in renewable-integrated microgrids. Unlike conventional methods that operate on fixed sampling intervals, event-based schemes activate corrective actions only when predefined thresholds are exceeded. This selective triggering reduces redundant computations and control signals, allowing efficient use of communication and hardware resources [59]. A general formulation of the trigger condition is expressed as (16).

$$\left|\left|x(t) - x(t_k)\right|\right| \geq \epsilon \tag{16}$$

Where $x(t)$ is the system state, $x(t_k)$ is the last sampled state, and epsilon (ϵ) defines the permissible error bound. Once this threshold is crossed, a new control action is issued; otherwise, the controller remains idle [60]. Additional variations of this formulation, including adaptive thresholds and multi-variable triggers, are provided in the supplementary material. The reviewed studies consistently highlight that event-based mechanisms enhance both stability and efficiency when integrated with state-space models and MPC. These approaches not only reduce computational demand but also extend device lifetimes by minimizing unnecessary actuation, particularly for converters and storage systems [61]. Beyond technical efficiency, event-triggered frameworks also improve resilience by focusing control resources on periods of actual system stress, such as sharp load changes or sudden renewable fluctuations. In summary, event-based control complements advanced state-space and predictive frameworks by offering a lean yet effective mechanism for dynamic stability management. Its selective nature minimizes overhead while preserving robustness, aligning well with the demands of distributed, renewable-driven grids.

5. CONCLUSION

This review examined how state-space modeling, real-time simulation, and advanced control strategies contribute to voltage stability in renewable-integrated microgrids. A central finding is that combining pre-synchronization techniques with MPC offers a dual-layered defense: Pre-synchronization ensures smooth phase and frequency alignment during grid transitions, while MPC delivers predictive adaptability to counteract renewable variability. Together, these mechanisms address both transient and steady-state

challenges that conventional controllers often fail to manage. The survey also highlights the emergence of event-based control frameworks, which complement state-space and MPC approaches by reducing redundant computations and extending the operational lifespan of converters and storage devices.

Despite these advances, practical deployment faces persistent challenges. High computational demands, reliance on accurate forecasting, and heterogeneous hardware infrastructures limit the scalability of real-time MPC frameworks. Addressing these issues will require hybrid solutions, integrating event-based schemes, FPGA acceleration, and adaptive impedance models, to balance precision with efficiency.

Looking forward, the integration of state-space models with real-time digital platforms and hardware-in-the-loop (HIL) testing provides a credible pathway for developing resilient, future-ready microgrids. By validating controllers against realistic operating scenarios, researchers and practitioners can better anticipate instability, optimize corrective strategies, and accelerate the transition toward low-carbon, high-reliability power systems.

Future research should prioritize scalable real-time frameworks that integrate FPGA-based acceleration with event-driven MPC to handle large-scale systems without prohibitive computational costs. Greater emphasis is also needed on co-simulation platforms that link transmission and distribution dynamics, enabling a holistic assessment of multi-level interactions. Additionally, as renewable penetration rises, cyber–physical security and the role of digital twins in predictive stability control deserve deeper investigation. Finally, comparative field validations across diverse microgrid topologies will be crucial for translating simulation-based findings into universally deployable design standards.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Ahmad Supawi Osman	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Aidil Azwin Zainul Abidin		✓				✓		✓	✓	✓	✓	✓		

C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
M	: **M**ethodology	R	: **R**esources	Su	: **Su**pervision
So	: **So**ftware	D	: **D**ata Curation	P	: **P**roject administration
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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Ahmad Supawi Osman ⓘ 🔀 SC ⓒ is a researcher at the Universiti Tenaga Nasional conduct on green technology innovation and sustainable energy generation in support of energy transition roadmap through developing and design renewable energy simulation algorithm for voltage stability in the presence of renewable energy. He can be contacted at email: ahmadsupawi@yahoo.com.

Aidil Azwin Zainul Abidin ⓘ 🔀 SC ⓒ is an expert in power system simulations that involve real-time simulators such as OPAL-RT and Speedgoat. These simulators utilize hardware-in-the-loop (HIL) techniques, allowing him to test protection relays in a controlled environment instead of the field. This method enables the testing of a broader range of operational scenarios. Additionally, he is actively involved in modeling protection relays within the Simulink environment as part of his research and simulation efforts. He can be contacted at email: aidilazwin@uniten.edu.my.