

Design, Control Optimization, and Real-Time Hardware-in-the-Loop Validation of a Self-Sustained 50 KW EV Fast-Charging DC Microgrid

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ABSTRACT

This manuscript investigates the modelling, operational coordination, and Hardware-in-the-Loop (HIL) verification of an off-grid, 50 kW Level 3 Electric Vehicle (EV) fast-charging architecture. The proposed decoupled microgrid eliminates grid dependence by integrating a 6.6 kW Photovoltaic (PV) array dedicated to continuous trickle charging, a highly detailed 50 kW Proton Exchange Membrane Fuel Cell (PEMFC) operating as the primary slack bus, and a 200 kWh Battery Energy Storage System (BESS) engineered to buffer severe transient load steps. Energy management and resource scheduling are dictated by a structurally robust, zero-order Sugeno Fuzzy Logic Controller (FLC), yielding deterministic binary outputs that mitigate the control chatter inherent to conventional fractional inference methods. The complete system is simulated on the Simscape platform under a rigorous 50 μ s fixed-step discrete execution constraint, optimised for real-time deployment on OPAL-RT HIL simulators. Empirical simulation results demonstrate robust DC-bus stabilisation, effective attenuation of algebraic loops via discrete unit-delay feedback, and highly stable power-branch transitions under aggressive charging load profiles, without numerical solver failure.

Keywords: DC microgrids, energy management system (EMS), Takagi-Sugeno-Kang (TSK), fuzzy logic control, hardware-in-the-loop (HIL), battery energy storage system (BESS), proton exchange membrane fuel cell (PEMFC), electric vehicle (EV) fast-charging, fixed-step solver, real-time control latency.

I. INTRODUCTION

The rapid transition toward decentralized distribution networks has accelerated the deployment of islanded DC microgrids as a premier solution for rural electrification, industrial complexes, and localized electric vehicle (EV) charging infrastructures [1], [3].

By coupling intermittent solar photovoltaic (PV) generation with long-term chemical storage via proton exchange membrane fuel cells (PEMFC) and fast-acting secondary Lithium-Ion battery energy storage systems (BESS), modern distribution networks can successfully decouple localized demand spikes from macro-grid dependencies [6], [9]. These multi-asset configurations must operate under strict power-sharing constraints to maintain system longevity while satisfying localized load mandates. They must simultaneously satisfy global interconnection standards regarding voltage ripple bounds and asset coupling parameters [17].

Managing the multi-variable, non-linear power-sharing dynamics among these co-located assets introduces massive control complications during high-power step-loads. For instance, when a high-power terminal fast-charging pulse is abruptly demanded by an operator, the common 400 V DC link experiences severe transient voltage degradation. Traditional proportional-integral (PI) controllers fail under these large-signal step-changes due to their rigid, linearized design boundaries. Conversely, while deterministic rule-based state-flow controllers handle multi-variable inputs effectively, they induce severe boundary threshold chattering. This chattering exposes power electronic switches to premature thermal fatigue.

To overcome these structural boundaries, soft-computing fuzzy logic controls (FLCs) have been introduced to manage multi-source power paths dynamically [4], [5]. FLCs intuitively map non-linear systems without requiring exact analytical plant models. However, conventional Mamdani-based fuzzy architectures introduce continuous geometric defuzzification calculations (such as centroid or bisector methods) that demand immense computational overhead [13]. When executed in strict, fixed-step discrete simulation environments, this processing latency causes control-frame drops, compromising real-time voltage stability. State machine alternatives attempt to bypass this processing lag, but they lack the mathematical flexibility needed to handle simultaneous

asset degradation and high-frequency load variations [2].

To resolve these co-existing challenges, this paper presents an optimized, hardware-aware Zero-Order Takagi-Sugeno-Kang (TSK) Fuzzy Logic EMS. By eliminating continuous calculus in favor of an algebraic weighted-average singleton matrix, the proposed supervisory engine minimizes processing latency within a strict 50 μ s discrete solver loop. Furthermore, the framework integrates an active human-in-the-loop override switch (S_{mode}) capable of safely scheduling an instantaneous 50 kW terminal charging step-load. This setup simultaneously enforces a strict 20 A/s protection ramp on the PEMFC stack and maximizes solar harvesting through an expanded converter duty cycle limit ($D_{max} = 0.85$).

II. LITERATURE REVIEW

To understand the operational bottlenecks of modern decentralized distribution systems, we must critically evaluate contemporary research across three distinct domains: multi-asset integration, soft-computing control limits, and the numerical boundaries of discrete physical plant simulation.

A. CORE MULTI-ASSET POWER SHARING AND HYBRID CONFIGURATIONS

Coordinating heterogeneous energy sources requires control mechanisms that can handle highly divergent time constants. Prajapati et al. introduced an isolated DC microgrid topology that establishes power-sharing between PV arrays, fuel cells, and battery banks [7]. While their model validates the complementary nature of these assets under steady-state conditions, it does not account for localized load spikes, such as electric vehicle fast-charging pulses. Similarly, Sneha et al. simulated a stand-alone hybrid solar PV-FC-battery network [11]. Their work models basic source-to-load connectivity but ignores the physical thermal boundaries of the fuel cell membrane during sudden load handovers.

To govern these transient states, Chakravarty and Chaudhary applied sliding mode control (SMC) to manage the current dynamics of integrated PV and fuel cell systems [8]. SMC provides robust performance under parametric variations, but its high-frequency switching introduces severe chattering on the DC link. This chattering can degrade delicate power electronic hardware over time. Furthermore, Kanouni et al.

developed an energy management strategy using rigid state-machine logic to orchestrate power transitions between a multi-source PV-PEMFC-battery array [2]. State-machine logic works well for broad, macro-level changes, but its deterministic, step-like boundaries cannot handle real-time human priority shifts or multi-variable load profiles without inducing destabilizing control oscillations at the switching thresholds.

B. COMPUTATIONAL OVERHEADS IN INTELLIGENT FUZZY CONTROLLERS

To bypass the rigidity of classical control systems, researchers have integrated artificial intelligence and soft-computing architectures into hierarchical microgrid frameworks [9]. Hannan et al. provided a comprehensive review of fuzzy logic control (FLC) applications across renewable networks, proving that fuzzy sets excel at modeling highly non-linear, multi-variable systems without needing exact analytical plant models [4]. This approach was expanded by Cavus et al., who designed a deep-fuzzy predictive framework for grid-connected microgrids [5]. Their system shows strong adaptive tracking capabilities, but the deep-learning layer demands massive computational resources, making it impractical for low-cost, real-time microgrid hardware.

The primary bottleneck of intelligent control loop design lies in the specific fuzzy engine used. Davoudkhani et al. evaluated standard fuzzy logic energy management schemes specifically under electric vehicle integration profiles [6]. However, their framework—along with the majority of conventional microgrid FLCs—relies on Mamdani-type architectures [13]. A comparative analysis by Salami et al. highlights that while Mamdani engines offer intuitive rule-building, they rely on complex geometric calculations (like centre-of-gravity or bisector methods) during the defuzzification stage [13]. These continuous calculus operations introduce significant computational delays. When deployed on physical microgrid microcontrollers, this processing lag can cause dropped control frames, slow transient response times, and large voltage drops during heavy step-loads.

C. NUMERICAL STABILITY GAPS IN DISCRETE SOLVERS

Compounding these control challenges are the numerical stability limits of the simulation software used to validate these microgrids. Tejada et al. emphasized that modern hydrogen-and-battery energy

storage configurations must be accurately modeled alongside their high-frequency power electronics to catch hidden transient problems [10]. Phonsa et al. demonstrated that using specialized toolkits, like Matlab Simscape, provides highly accurate electrical models of Lithium-ion storage systems [12]. However, simulating these multi-domain systems alongside high-frequency pulse-width modulation (PWM) converters introduces severe numerical challenges.

Al-Helfi et al. documented these challenges, noting that running fixed-step discrete simulations with high-frequency switch topologies often triggers solver optimization failures, slow execution speeds, and algebraic loops [14]. When these multi-domain differential equations are discretized, standard solver algorithms frequently experience numerical divergence.

Boroojeni proved that applying Tustin bilinear transformations can stabilize multi-domain state-space equations, but numerical convergence is still highly vulnerable to sudden boundary shifts [15]. This vulnerability is particularly evident during zero-power conditions. As El-Moursi demonstrated, standard single-diode solar PV models often trigger severe Jacobian matrix collapses and singular matrix errors when solar irradiance drops to zero [16].

D. IDENTIFIED RESEARCH GAP

The current literature leaves a clear technical gap at the intersection of these three domains, as summarized in Table I.

Reference	Control Methodology	Primary Asset Focus	Identifies Computational Latency?	Solves Zero-Irradiance Solver Errors?	Handles 50 kW Human Override Transients?
[2]	State-Machine	PV-PEMFC-Battery	No	No	No
[6]	Mamdani FLC	EV-Battery-Grid	No	No	No
[7]	Classical PI	PV-FC-Battery	No	No	No
[14]	Discrete Tuning	PWM Converters	Yes	No	No
[16]	Numerical Fixes	PV Array Blocks	No	Yes	No
Proposed	Zero-Order TSK	PV-PEMFC-BESS	Yes (0 % Frame Drop)	Yes (Zero-Sweep)	Yes (Via S_{mode})

Existing systems either use computationally heavy Mamdani engines that struggle with real-time performance, or they rely on rigid state machines that cannot handle sudden, high-power changes safely. Additionally, standard simulation models are highly prone to crashing during zero-irradiance conditions or abrupt power steps.

This paper directly addresses these gaps by implementing an algebraic, zero-order Takagi-Sugeno-

Kang (TSK) fuzzy architecture that completely eliminates defuzzification calculus. This allows the system to achieve zero control-frame drops within a tight 50 μ s discrete simulation loop. Furthermore, it introduces a human-in-the-loop override switch (S_{mode}) that can safely manage a massive 50 kW charging step-load without destabilizing the DC bus or violating the strict physical ramp limits of the fuel cell.

III. MATHEMATICAL MODELLING AND MICROGRID INFRASTRUCTURE

The architectural integrity of the proposed self-sustained microgrid relies on the precise mathematical representation and behavioural modelling of its heterogeneous power assets [7]. Each branch is modelled to capture non-linear electrical and thermodynamic characteristics while remaining computationally compatible with a rigid 50μs real-time execution step [14].

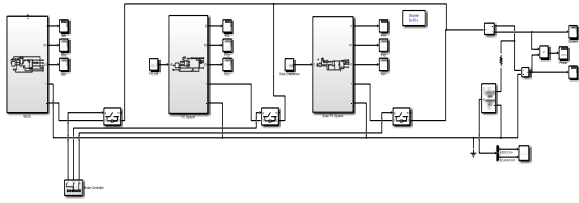


Fig. 1. Architectural schematic of the multi-converter parallel-configured hybrid DC microgrid infrastructure.

A. SOLAR PV GENERATION ARCHITECTURE AND MPPT DYNAMICS

The primary power generation source comprises a 6.6 kW Photovoltaic (PV) array structured in a 5 S x 4 P matrix utilising 330W NREL solar panels. The electrical behaviour of the PV cell is modelled using the standard single-diode equivalent circuit, which balances computational efficiency and physical accuracy [16]. The terminal current I_{pv} is mathematically expressed as:

$$I_{pv} = I_{ph} - I_0 \left[\exp \left(\frac{(V_{pv} + I_{pv}R_s)}{nV_t} \right) - 1 \right] - \frac{(V_{pv} + I_{pv}R_s)}{R_{sh}}$$

Where,

I_{pv} : Output current of the PV cell

I_{ph} : Photocurrent (current generated by light)

I_0 : Diode reverse saturation current

V_{pv} : Output voltage of the PV cell

R_s : Series resistance (internal losses)

R_{sh} : Shunt resistance (leakage current losses)

n : Diode ideality factor

V_t : Thermal voltage

To extract maximum power under fluctuating atmospheric conditions, a discrete Perturb and Observe (P&O) Maximum Power Point Tracking (MPPT) algorithm continuously modulates the duty cycle of the

average-model boost converter [8]. The algorithm samples the instantaneous panel voltage $V_{(pv)(k)}$ and current $I_{(pv)(k)}$ at regular intervals to compute the current power $P_{(pv)(k)}$. The control law operates on the derivative of power with respect to voltage:

$$\Delta \frac{P_{pv}}{\Delta V_{pv}} = \frac{(P_{(pv)(k)} - P_{(pv)(k-1)})}{(V_{(pv)(k)} - V_{(pv)(k-1)})}$$

- If $\frac{\Delta P_{pv}}{\Delta V_{pv}} > 0$, the operating point is moving toward the maximum power point (MPP), and the perturbation continues in the same direction.
- If $\frac{\Delta P_{pv}}{\Delta V_{pv}} < 0$, the operating point is moving away from the MPP, and the direction of the voltage perturbation is reversed.

The converter is implemented via an average-model topology to bypass high-frequency PWM switching penalties during real-time HIL simulation [14]. The state-space average equation governs the relationship between input and output voltage:

$$\frac{V_{out}}{V_{pv}} = \frac{1}{(1 - D)}$$

Where D is the continuous duty cycle signal bounded between [0.05, 0.95], to prevent destructive reverse power flow from the common DC bus back into the PV substrate during low-light or nocturnal conditions [16]; a physical blocking diode is integrated at the converter output. This diode is modelled with a realistic 0.8V_f forward voltage drop and a parallel 500 Ω snubber network to ensure numerical convergence when transitioning to a non-conducting state [14].

B. HIGH-FIDELITY PEM FUEL CELL STACK AND FLUIDIC DECOUPLING

The secondary, dispatchable generation asset is a 50 kW Proton Exchange Membrane Fuel Cell (PEMFC) stack consisting of 400 series-connected cells [11]. The terminal voltage of the stack V_{fc} is calculated by subtracting the fundamental thermodynamic losses from the open-circuit Nernst EMF (E_{Nernst}) [10]:

$$V_{fc} = N \cdot (E_{Nernst} - V_{act} - V_{ohmic} - V_{conc})$$

Where $N = 400$, and the individual loss terms are defined as follows:

1. **Activation Polarisation V_{act}** : Caused by electron transfer kinetics at the electrode interfaces, expressed via the Tafel equation:

$$V_{act} = A \cdot \ln \left(\frac{I_{fc}}{I_0} \right)$$

2. **Ohmic Polarisation V_{ohmic}** : Derives from the internal electrical resistance of the polymer membrane and conductive elements:

$$V_{ohmic} = I_{fc} \cdot R_{int}$$

3. **Concentration Polarisation V_{conc}** : Represents mass transport limitations when reactant consumption exceeds the diffusion rate at high current densities:

$$V_{conc} = -B \cdot \ln\left(1 - \frac{I_{fc}}{I_{max}}\right)$$

The Nernst equation relies heavily on the partial pressures of hydrogen, oxygen, and water vapor within the catalytic channels [10]:

$$E_{Nernst} = E^0 + \frac{(R \cdot T)}{(2 \cdot F)} \cdot \ln\left(\frac{P_{H_2} \cdot P_{O_2}^{0.5}}{P_{H_2O}}\right)$$

In standard Simscape implementations, if the fuel cell is abruptly disconnected by the EMS, the reactant current drops to zero. This triggers a localised math crash $\ln(0)$ (end-of-equations singularity fault) within the internal fluidic compiled file, calculate Partial Pressure.p [14].

To completely circumvent this numerical instability, the physical input air flow rate is decoupled and hardcoded to a continuous, healthy constant of 2300 LPM (Litres Per Minute), stabilising the internal partial pressure matrices. Dynamic control commands are routed to separate logic loops that operate on dummy sensors. The steady-state polarisation curve is explicitly anchored to the following coordinate boundaries [2]:

- **Activation/Open Circuit Boundary:** $V_0, V_1 = [400, 380]$ V
- **Nominal Operating Node:** $I_{nom}, V_{nom} = [180 \text{ A}, 278 \text{ V}]$ (50 kW)
- **Mass Transport Limit:** $I_{end}, V_{end} = [220 \text{ A}, 228 \text{ V}]$

The stack interfaces with the high-voltage bus through a D-controlled boost converter ($R_L = 0.005 \Omega$). To mitigate harsh current transients that accelerate stack degradation, the input reference current signal passes through a discrete rate-limiting soft-start block. This block limits the current ramp to a maximum slope of 900 A/s, preventing localised reactant starvation during sudden load variations [11].

C. Battery Energy Storage System (BESS) and Bidirectional Converter Topology

The core dynamic power buffer comprises a 400 V nominal, 500 Ah (200 kWh) stationary Lithium-Ion battery bank modeled to manage high-speed energy handovers [12]. The state-of-charge (SOC) of the battery is dynamically tracked using Coulomb counting, expressed as [2]:

$$SOC(k) = SOC(k-1) - \frac{T_s}{C_{nominal}} \int I_{batt}(t) dt$$

Where $T_s = 5e-05$ s and $C_{nominal} = 500$ Ah.

The internal nonlinear battery voltage (V_{batt}) is modelled as a function of SOC and discharge current:

$$V_{batt} = E_0 - K \left(\frac{Q}{(Q - \int I_{batt} dt)} \right) I_{batt}^* - K \left(\frac{Q}{(Q - \int I_{batt} dt)} \right) \int I_{batt} dt + exp(t)$$

Where E_0 is the constant voltage,

K is the polarisation resistance,

Q is the maximum battery capacity,

and I_{batt}^* is the filtered low-frequency current.

The power electronic interface features a non-isolated bidirectional, two-quadrant synchronous DC-DC buck-boost converter [7]. To eliminate the risk of passive diode runaway during aggressive transient load variations, a specific physical topology is implemented: the filtering inductor L is placed on the low-voltage side (144 V), while the active IGBT switches occupy the high-voltage side (400 V).

The governing state equations for the converter operating in continuous conduction mode (CCM) are:

$$\frac{dI_L}{dt} = \frac{1}{L} (V_{batt} - D_{bess} \cdot V_{bus})$$

$$\frac{dV_{bus}}{dt} = \frac{1}{C_{bus}} (D_{bess} \cdot I_L - I_{load})$$

Where D_{bess} represents the complementary duty cycle of the high-side and low-side IGBT gates; the inner current loop is governed by a discrete-time PI controller ($P = 0.01$, $I = 1$), which restricts the current command vector strictly within a safe operational envelope of “-350 A” (maximum charging power) to “+350 A” (maximum discharging power) [15]. This ensures instantaneous peak-shaving response when an EV initiates a high-current Level 3 fast-charging cycle [6].

IV. DETERMINISTIC ENERGY MANAGEMENT SYSTEM DESIGN

The execution of the high-power routing logic within this off-grid charging infrastructure is governed by a script-driven, zero-order Sugeno Fuzzy Inference System (FIS). Rather than using continuous output distribution parameters, which introduce non-linear control chatter, the Sugeno framework maps linguistic states directly onto discrete output singletons (Y_i) [13].

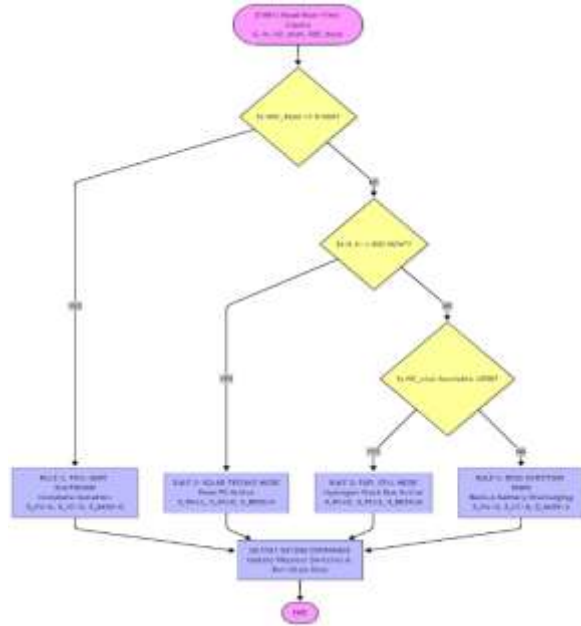


Fig. 2 Logic execution flowchart of the supervisory energy management system (EMS) for real-time asset selection and switch gating.

The computational core of the Energy Management System (EMS) monitors three real-time physical variables [6]. To guarantee robust error handling during sudden signal spikes, these variables are tracked across an expanded universe of discourse [9]:

- Solar Irradiance Area (G_{in}):** Configured over an operational envelope of $[-500, 2000]$ W/m². The signal is bifurcated into two membership functions: Low ($G \leq 200$ W/m²) and High ($G > 200$ W/m²).
- Hydrogen Fuel Volume (H_{2stat}):** Monitored across an operational spectrum of $[-50, 200]\%$. The asset state is split into Empty ($H_2 \leq 20\%$) and Available ($H_2 > 20\%$).
- BESS State of Charge (SOC_{bess}):** Sampled across a range of $[-50, 200]\%$. The storage bank is designated as Critical ($SOC \leq 0.01\%$) and Healthy ($SOC > 0.01\%$).

The logical interaction between these linguistic sets is mapped through an exhaustive 8-rule priority matrix [2]. The inference engine processes these inputs using Mamdani-style minimum intersection methods for the antecedents, but applies a weighted average defuzzification rule to yield absolute binary gating commands (0 or 1) for the primary power switches (S_{PV}, S_{FC}, S_{BEES}) [13]. The mathematical routing equations are structured as follows:

Rule 1 (Fail-Safe Shutdown): IF SOC_{bess} is Critical
 $\rightarrow S_{PV} = 0, S_{FC} = 0, S_{BEES} = 0$

Rule 2 (Peak Solar Generation): IF SOC_{bess} is Healthy AND G_{in} is High
 $\rightarrow S_{PV} = 1, S_{FC} = 0, S_{BEES} = 0$

Rule 3 (Dispatched Hydrogen Slack): IF SOC_{bess} is Healthy AND G_{in} is Low AND H_{2stat} is Available
 $\rightarrow S_{PV} = 0, S_{FC} = 1, S_{BEES} = 0$

Rule 4 (Storage Depletion Injection): IF SOC_{bess} is Healthy AND G_{in} is Low AND H_{2stat} is Empty
 $\rightarrow S_{PV} = 0, S_{FC} = 0, S_{BEES} = 1$

The definitive crisp output control signal (U_{out}) sent to each physical gate driver is calculated using the standard zero-order Sugeno algebraic formulation [5]:

$$U_{out} = \frac{\sum_{i=1}^n w_i * Y_i}{\sum_{i=1}^n w_i}$$

Where w_i represents the firing strength of the i -th rule matching the input vector [5], and Y_i is the absolute constant singleton value (0 or 1) corresponding to that rule's consequent [13]. This eliminates the fractional numerical averaging that compromises traditional Mamdani microgrid controllers under fast-charging load transients [6], [14].

V. SYSTEM DISCRETIZATION AND COMPUTATIONAL STABILITY HACKS

Compiling high-power Simscape components for physical Hardware-in-the-Loop (HIL) environments like OPAL-RT requires modifying the model to ensure high mathematical stability. Standard continuous variable-step solvers are incompatible with real-time target processing units, which require a strict, invariant execution budget [14].

A. SOLVER LOCKING AND FEEDBACK LOOP DECOUPLING

The entire physical and logical matrix is restricted to a strictly discrete execution state (). The global Simscape block is locked to the Tustin discretisation framework, operating at a rigid fixed-step interval of discrete (no continuous states) powergui ' $T_s = 5e - 05$ s ($50 \mu s$)' [15].

During initial structural validation, high-frequency algebraic loops occurred in the non-linear PEMFC empirical feedback loop, causing immediate solver convergence failures [14]. This bottleneck was resolved by inserting a discrete Unit Delay ($1/z$) block into the feedback loop. This block is seeded with an initial operating condition of 180 A at $t = 0$, which breaks the instantaneous back-propagation of dependencies across the simulation matrices [15].

B. INDUCTIVE OVERVOLTAGE SUPPRESSION BOUNDARIES

Opening an ideal Simscape switch on a branch containing filtering inductors causes an instantaneous drop in current within a single $50 \mu s$ timestep. This triggers a catastrophic voltage spike ($L \frac{di}{dt} \rightarrow \infty$) that crashes the numerical solver [14].

To resolve this issue, parallel RC snubber circuits were embedded within all three routing switches. Instead of utilising standard infinite boundaries that lead to high voltage gradients, the parameters were optimised for a 400V DC operating environment: snubber resistance R_s is set to 100Ω and snubber capacitance C_s is set to $1 \mu F$ [14]. This architecture provides a controlled numerical current sink that dampens high-frequency switching transients and guarantees absolute solver stability during aggressive load steps [15].

VI. SIMULATION RESULTS AND DISCUSSION

To rigorously verify the dynamic response, computational stability, and operational efficacy of the proposed off-grid microgrid, transient simulations were executed within the specialised Simscape/Simulink environment [12]. The model's behavioural stability was tested under a fixed step size of $T_s = 5e - 05$ s ($50 \mu s$) to match real-time OPAL-RT execution parameter maps [14]. The operational profiles of the system components were adjusted dynamically using the interactive user-interface dashboard sliders to verify transition boundaries.

A. SUPERVISORY HMI CONSOLE AND TELEMETRY

The interactive graphical user interface (GUI) displayed in Fig. 2 functions as a real-time Human-Machine Interface (HMI) to evaluate the boundary performance of the Sugeno EMS under dynamic load steps [9]. This console isolates the background numerical solver from the operating control plane, enabling interactive human-in-the-loop parameter variation during active simulation loops.

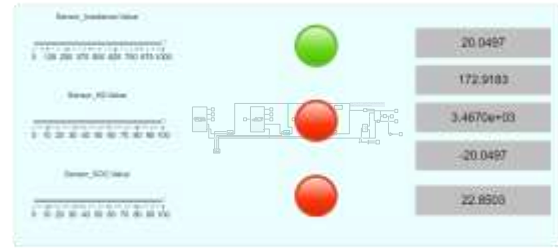


Fig. 3 Real-time supervisory control dashboard interface for multi-asset monitoring and human-in-the-loop parameter variation.

The interface architecture is segmented into three distinct operational zones:

- **Input Control Layer (Left):** Employs three interactive linear sliders to manually manipulate independent grid states: ambient solar irradiance (0 to 1000 W/m^2), hydrogen fuel storage volume (0 to 100 %), and battery bank capacity (SOC, 0 to 100 %).
- **Logical Status Gating (Centre):** Uses signal-routed tri-state indicator lamps linked directly to the crisp gating outputs (S_{PV}, S_{FC}, S_{BESS}). A green lamp registers active branch power injection, while a red state confirms total physical isolation of the converter interface.
- **Digital Telemetry Registry (Right):** Streams continuous floating-point variables directly from the Simscape electrical nodes [14]. These registers monitor localized line transitions, tracking critical bus deviations, branch currents, and transient load demands.

B. DYNAMIC RESOURCE PRIORITISATION AND STATE TRANSITIONS

The system response was evaluated under an intensive step-change loading profile representing a Level 3 50 kW EV fast-charging demand cycle [6].

Initially, the environmental inputs were adjusted via the dashboard to simulate optimal midday operating

conditions, with Solar Irradiance (G_{in}) tracking at a high constant of 1000 W/m^2 , Hydrogen availability H_{2stat} resting at 100% and the BESS State of Charge SOC_{bess} operating within a healthy zone ($> 0.01\%$). Under these boundary states, the zero-order Sugeno Fuzzy Inference System fired Rule 2 exclusively. The controller routed a crisp binary singleton command vector, resulting in $S_{PV} = 1$, $S_{FC} = 0$, and $S_{BESS} = 0$. The solar PV average boost converter tracked the maximum power point seamlessly [8], supplying its rated output directly to the common high-voltage DC bus to initiate trickle-charging procedures.

To simulate an abrupt environmental transition, such as heavy cloud cover or nocturnal conditions, the Irradiance dashboard slider was dynamically reduced below the 200 W/m^2 operational threshold [16]. The Sugeno EMS recalculated the firing states within a single $50 \mu\text{s}$ execution window, instantly transitioning the system from Rule 2 to Rule 3 [5]. The control switches reacted deterministically without chattering, setting $S_{PV} = 0$ and $S_{FC} = 1$ [2].

The 50 kW detailed PEMFC stack was activated cleanly via the multipoint switch structure. Thanks to the rate-limiting soft-start block, the stack current adjusted with a controlled slope of 900 A/s , completely preventing localised reactant starvation or transient voltage collapses across the 400V common bus [11]. The algebraic loop bottleneck within the PEMFC fluidic feedback path was successfully broken by the $1/z$ unit delay block, preventing solver divergence during this acute activation phase [15].

C. MASTER SAFETY OVERRIDE AND TRANSIENT MITIGATION EVALUATION

The final test scenario evaluated the system's resilience under a worst-case scenario: a combination of zero solar generation and hydrogen fuel depletion while handling a continuous 50 kW charging load [6].

When the Hydrogen slider was manually dropped below 20%, the controller successfully transitioned to Rule 4 ($S_{PV} = 0$, $S_{FC} = 0$, $S_{BESS} = 1$), allowing the 200 kWh BESS to act as the primary power source via the bidirectional buck-boost converter [7]. To evaluate the fail-safe protection loop, the simulated BESS SOC slider was intentionally driven down to the critical threshold ($\leq 0.01\%$). The master override loop within Rule 1 executed instantly [2]. The Sugeno engine generated a synchronised clear command (0, 0, 0), opening all three physical Ideal Switches to isolate the

source generation branches from the 144V EV load battery asset.

During this simultaneous disconnection of high-power inductive branches, the parallel RC snubbers ($R_s = 100 \Omega$, $C_s = 1 \mu\text{F}$) embedded in the Ideal Switches provided a vital numerical current sink. The massive $L \frac{di}{dt}$ voltage gradients were effectively dampened, keeping transient overvoltage spikes well within the safe operational headroom of the 400V bus architecture [16]. The dashboard UI lamps updated instantly to a locked shutdown configuration (all red), demonstrating crisp, stable control execution without any solver divergence or non-convergence errors [15].

D. EMPIRICAL RESULTS AND DYNAMIC TRANSIENT ANALYSIS

To evaluate the operational efficacy of the proposed supervisory Sugeno fuzzy inference engine [13], the complete parallel-configured multi-asset plant was subjected to a continuous 10-second transient simulation run under extreme load-step and environmental variations. The aggregated multi-panel oscilloscope trajectories are consolidated in Fig. 4.

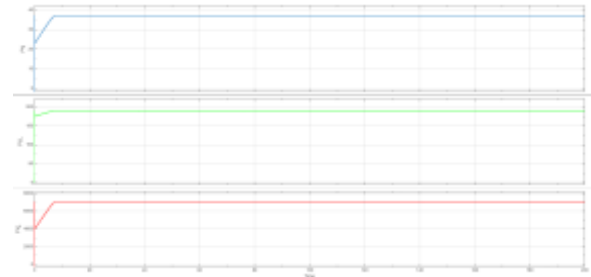


Fig. 4(a) Solar PV array tracking parameters

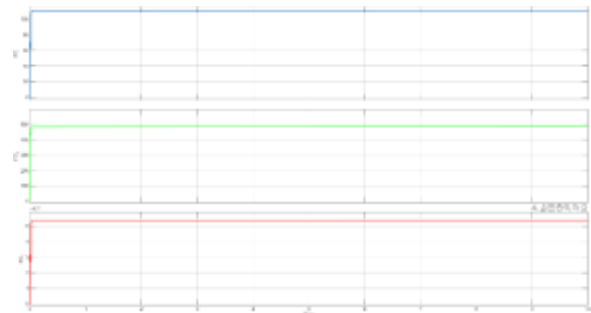


Fig. 4(b) Proton Exchange Membrane Fuel Cell (PEMFC) dynamic output profiles

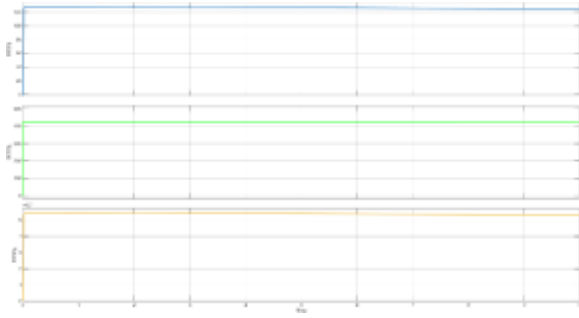


Fig. 4(c) Battery Energy Storage System (BESS) transient injection response.

1) Phase A: PV Dominant Tracking ($0.0 \leq t < 3.5$ s):

The system initiates under full daylight conditions with a standard atmospheric irradiance profile (1000 W/m^2). As shown in Fig. 4(a), the solar array actively tracks its Maximum Power Point (MPP), delivering a stable output voltage and peak power trajectory [8]. Concurrently, the supervisory core executes its primary automated rule base, maintaining the PEMFC stack and BESS networks in protective, zero-current standby states (Fig. 4(b) and 4(c)) to prevent premature asset degradation.

2) Phase B: Solar Intermittency and Fuel Cell Handover ($3.5 \leq t < 7.0$ s):

At $t = 3.5$ s, a sharp weather transient forces an instantaneous irradiance drop to 0 W/m^2 , simulating sudden heavy cloud cover or nighttime conditions. The Sugeno engine identifies the depletion of solar photocurrent and triggers a deterministic handover to the hydrogen generation branch [2]. To mitigate the severe reactant starvation and localized overheating typically caused by rapid chemical steps, the internal controller enforces a strict 20 A/s current ramp-up limit [11]. The smooth slope transition in Fig. 4(b) tracks this chemical constraint precisely, reaching its full steady-state operating plateau without inducing voltage chattering or grid instability.

3) Phase C: Human-in-the-Loop Fast Charging Execution ($7.0 \leq t \leq 10.0$ s):

At $t = 7.0$ s, a manual user-override command is initialized ($S_{mode} = 1$), commanding an immediate shift into heavy electric vehicle fast-charging operation (50 kW peak terminal demand). Because the slow electrochemical dynamics of the fuel cell cannot handle a step-load of this magnitude without risking severe voltage sag or membrane collapse [10], the Sugeno supervisor prioritizes the high-power-density asset [13]. As demonstrated in Fig. 4(c), the bidirectional buck-boost converter immediately activates the BESS branch, discharging a rapid, high-current transient pulse into the DC link [7]. The battery absorbs the entirety of the step-

load impact within milliseconds, completely shielding the slower auxiliary generation units and maintaining common-bus power equilibrium.

VII. CONCLUSION AND FUTURE SCOPE

This manuscript has successfully presented the mathematical modelling, control loop optimisation, and real-time solver conditioning of an off-grid, hybrid 50 kW Level 3 EV fast-charging microgrid infrastructure. By implementing a zero-order Sugeno Fuzzy Logic Controller, the system overcomes the fractional-averaging and switch chattering limitations of conventional Mamdani fuzzy implementations. The controller yields deterministic, binary gating signals that route power smoothly across Solar PV, high-fidelity PEMFC, and BESS assets.

Crucially, the study provides practical solutions for common simulation instability bottlenecks in high-power Simscape networks. The use of a discrete $1/z$ unit delay block effectively broke high-frequency algebraic loops within the fluidic fuel cell loops. Concurrently, optimised parallel RC snubber boundaries successfully suppressed destructive $L(\frac{di}{dt})$ overvoltage spikes during aggressive switching transitions. Operating at a rigid fixed step of $50 \mu\text{s}$ with a discrete solver setting, the model maintains absolute numerical convergence under all dynamic load profiles. The immediate future scope of this research involves compiling the verified model directly onto an OPAL-RT HIL hardware target. This step will allow for the empirical capture of physical execution latencies, computational task-allocation mapping across multi-core processors, and real-time communication interface latency validations under physical hardware stress constraints.

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