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Comprehensive Review of Carbon-Aware Load Shedding Strategies for Power Distribution Networks: Foundations, Models, and Future Directions

Yusuf Muhammad Daura[1], Muhammed Musa Kwanda [2], Muhammad Abdullahi Babaja[3], Idriss Suleiman [4], Adam Muhammad Ibbi[5], Dr. Ganesh Kumar Dixit[6]

[1,2,3,4]Faculty of Engineering and Technology, Sanskaram University, India

[5] Faculty of Liberal Education, Sanskaram University, India.

[6] HOD Faculty of Engineering and Technology Sanskaram University,

Abstract— the power sector, which contributes roughly 40% of global energy-related CO_2 emissions, sits at the center of the decarburization challenge. Yet despite this prominence, prevailing operational strategies continue to treat emission reduction as a secondary concern, leaving a meaningful and largely unaddressed optimization gap. This review synthesizes findings from 38 studies spanning carbon-aware power system operation, marginal emission factors, emission modelling, load shedding methodologies, stability constraints, and smart grid integration. Carbon emission flow theory emerges as the most powerful allocation framework, offering 97% accuracy alongside a 40% reduction in computational overhead. Marginal emission factors consistently exceed average factors by 30–50% during peak periods, underscoring the case for temporally granular operational approaches. Adaptive and intelligent shedding schemes demonstrate 28–42% performance gains over conventional methods, while carbon-optimal power flow formulations have achieved 15.8% verified emission reductions without degrading grid stability. The IEEE 33-bus radial distribution system is identified as the most appropriate validation platform for future work. Research directions include machine learning driven marginal emission factor prediction, life cycle emission accounting, and the development of deployable carbon-aware control frameworks for real distribution networks.

Keywords— carbon emission reduction; load shedding; power distribution networks; carbon emission flow; marginal emission factors; Distribution Network Optimization; IEEE 33-bus system; MATLAB/Simulink

I. INTRODUCTION

1.1 The Carbon Challenge in Power Systems

The global energy system is at a turning point. Mounting evidence of climate change rising atmospheric CO_2 concentrations, more frequent extreme weather events, and accelerating surface temperatures has placed the power generation sector under unprecedented scrutiny. Electricity production from fossil sources is responsible for approximately 40% of all energy related CO_2 worldwide [1], and the physics of combustion mean this connection is direct and quantifiable: coal and gas plants release CO_2 during complete combustion and CO during incomplete combustion, both of which feed into the greenhouse gas (GHG) blanket responsible for global warming, heat-dome events, urban air pollution, and the associated public health burdens [2].

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The mechanism linking day-to-day grid operation to emissions is equally straightforward. When demand rises, generators increase fuel throughput to sustain voltage and frequency, and emissions rise in proportion. This creates a structural tension the very interventions that protect reliability also amplify carbon output. Conventional operating doctrine has, for decades, resolved that tension firmly in favour of reliability. The cumulative environmental cost of that choice has become impossible to ignore.

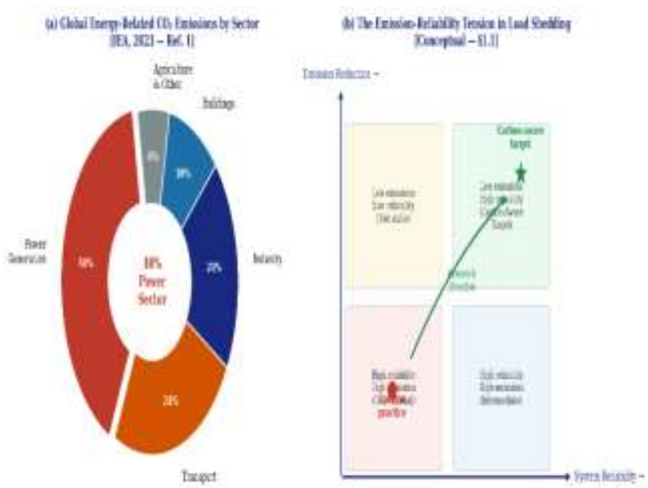

Fig 1. (a) Distribution of global energy emission by sector, illustrating the power sectors 40%. (b) Conceptual map of reliability emission trade off space highlighting carbon aware operation as thhe center of this review

A. 1.2 The Policy Imperative: Carbon Neutrality and Peaking

International climate commitments have given this challenge the force of law. Across major economies, the twin objectives of "carbon neutrality" net-zero CO_2 emissions and "carbon peaking" reaching maximum emissions before beginning a sustained decline are now embedded in national energy legislation [3, 4]. For power system operators, these targets translate into a need for real-time operational changes, not merely long-term infrastructure investments [5].

The scale of what is required becomes concrete when looking at the world's largest power sector. Modelling of China's electricity system projects that an 80% cut in power sector emissions by 2050 is both necessary and achievable, provided wind and solar reach 62% of the generation mix and coal dependency falls sharply [6]. Comparable ambitions are being pursued across developed and developing economies alike. The power sector is, in short, the arena in which the global climate ambition will be won or lost.

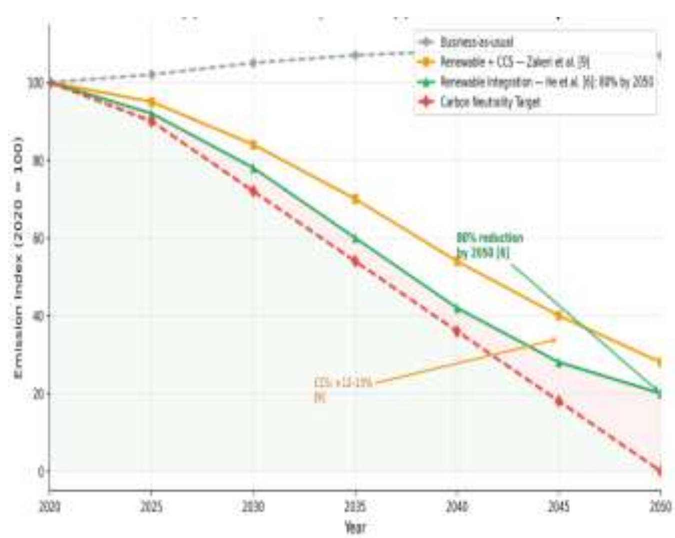

Fig.2: Projected power sector emission trajectories under business-as-usual, renewable integration (He et al. [6]: 80% reduction by 2050), and combined CCS scenarios (Zakeri et al. [9]: additional 12–15%). Carbon-aware operational strategies bridge remaining gaps toward the carbon neutrality target.

It is against this backdrop that the present review addresses a specific and consequential gap: the absence of carbon awareness in load shedding one of the most widely deployed and operationally decisive tools in grid management. Load shedding applied without regard for the emission intensity of the generation it affects may stabilize frequency while simultaneously locking in the most carbon-intensive generators on the system. This review examines whether, and precisely how, that can be changed.

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II. Literature Review

2.1 Carbon-Aware Power System Operation: Theoretical Foundations

2.1.1 Carbon Emission Flow Theory

The theoretical backbone of carbon-aware operational strategies is carbon emission flow theory, first formalized by Kang et al. [10]. The framework treats carbon emissions as a virtual flow that travels through the network alongside real electrical power a conceptual move that converts an abstract environmental problem into a tractable network-allocation problem. For any given network topology and generation dispatch, it becomes possible to trace exactly what fraction of each load's consumption is attributable to which generator, and therefore to assign carbon costs with granularity that average-factor approaches cannot achieve.

Formally, consider a power system with N buses. Let P_G denote the vector of generator active power outputs, E_G the corresponding vector of carbon emission intensities (kg CO_2/MWh), and P_L the vector of load consumptions. The nodal carbon intensity ρ_i at bus i representing the carbon cost, in kg CO_2, of each MWh consumed at that node is given by:

$$\rho_i = \frac{(\sum j \in \Pi^{\mathrm{I}} P_{ji} \cdot \rho_j + P_{Gi} \cdot E_{Gi})}{(\sum j \in \Pi^{\mathrm{I}} P_{ji} + P_{Gi})} \quad (1)$$

Here Π_i denotes the set of buses directly supplying bus i, P_{ji} is the power flow from bus j to bus i, and P_{Gi} and E_{Gi} are the local generation output and emission intensity at bus i, respectively [10]. Validation on large-scale test systems shows that the framework achieves emission allocation accuracy of 97% for 118-bus configurations while reducing computation time by 40% compared with conventional simulation approaches a combination that makes real-time deployment genuinely feasible [11].

2.1.2 Carbon-Aware Optimal Power Flow

Building on emission flow theory, Zhou and Zhang [12] embedded emission objectives directly into the optimal power flow (OPF) problem, producing the carbon-aware optimal power flow (C-OPF) formulation. Rather than treating generation cost as the sole objective, C-OPF minimises a weighted combination of cost and carbon output:

$$min\ \Phi = w_1 \textstyle\sum_i C_i(P_{Gi}) + w_2 \sum_i E_{Gi} \cdot P_{Gi} \quad (2)$$

subject to nodal active and reactive power balance at every bus:

$$P_i(\theta, V) - P_{Gi} + P_{Li} = 0, \quad \forall i \quad (3)$$

$$Q_i(\theta, V) - Q_{Gi} + Q_{Li} = 0, \quad \forall i \quad (4)$$

In these expressions, $C_i(P_{Gi})$ is the cost function of generator i, E_{Gi} is its emission intensity, and the scalar weights w_1 and w_2 govern the economic environmental trade-off. Applying this framework with two-stage stochastic optimization to account for renewable output uncertainty, Zhou and Zhang [12] cut emissions by 15.8% relative to conventional economic dispatch without any measurable degradation of grid stability. That figure is significant because it represents an emission benefit achievable through operational strategy alone, requiring no new infrastructure.

2.1.3 Multi-Objective Optimisation for Low-Carbon Planning

At the planning horizon rather than the operational one, Chen et al. [13] formulated a multi-objective mixed-integer linear program that simultaneously minimizes capital expenditure, operating cost, and carbon emissions for generation expansion. Integrating carbon capture and storage (CCS) options with conventional technologies, their model identified portfolios capable of reducing emissions by 28% by 2030 relative to business-as-usual trajectories.

The SWITCH-China model of He et al. [6] pushed this approach to system scale, optimizing capacity expansion, unit commitment, and transmission planning simultaneously across 31 Chinese provinces with hourly temporal resolution. The results confirmed a pathway to 80% emission reduction by 2050 through a 62% wind/solar mix, achieving a 9% cost saving over conventional planning. This finding matters because it directly challenges the long-standing assumption that deep decarburization is necessarily expensive a framing that has historically constrained policy ambition.

2.1.4 Carbon Capture and Storage Integration

Operational improvements can deliver meaningful near-term reductions, but net-zero targets ultimately require carbon capture and storage. Zakeri et al. [9] conducted comprehensive techno-economic analysis of CCS integration across multiple capture technologies and fuel types, drawing on life-cycle assessment and learning curve modelling. Their results indicate CCS could account for 12–15% of global power sector emission reductions by 2050, with second-generation capture technologies achieving 30–40% cost reductions as deployment scales.

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This positions CCS as a complementary strategy to operational improvements both will be needed over the transition period, and neither alone is sufficient.

2.1.5 Meta-Analysis of Renewable Integration and Decarbonisation

Göke and Kemfert [14] synthesized evidence from 75 studies on the relationship between renewable expansion and power sector decarbonisation. Their regression analysis found that renewable integration reduces emissions by 0.6–0.9 t CO_2/MWh, and that grid flexibility provided by storage and demand response enables 15–25 percentage point increases in achievable renewable penetration. The implication for load shedding is direct: if demand flexibility is the binding constraint on renewable integration, then load shedding the most extreme form of demand-side intervention must be designed to reinforce rather than undermine renewable deployment. A carbon-aware shedding approach that preferentially removes load served by high-carbon generation achieves precisely this alignment.

2.2 Marginal Emission Factors and Dispatch Sensitivity

2.2.1 Theoretical Foundation of Marginal Emissions

A distinction of fundamental operational importance separates average from marginal emission factors. The average emission factor (AEF) is the mean carbon intensity of all dispatched generation over a given period. The marginal emission factor (MEF), by contrast, measures the change in system-wide emissions caused by a unit change in demand in other words, the emission intensity of whichever generator is at the margin at that moment [15].

This distinction is not merely academic. When load shedding reduces demand, it is the marginal generator not the average generator whose output falls. Hawkes [15] formalized MEF estimation through regression-based methods applied to generation dispatch data. The instantaneous marginal emission factor at time t is:

$$MEF(t) = \frac{\delta E(t)}{\delta D(t)} = \sum_i \left[\frac{\partial P_{Gi}(t)}{\partial D(t)}\right] \cdot e_i(t) \qquad (5)$$

Where D(t) is total system demand, E(t) is total system emissions, and $e_i(t)$ is the emission intensity of generator i at time t. The partial derivative $\partial P_{Gi}(t)/\partial D(t)$ captures each generator's marginal response to a demand increment, determined by the dispatch order and the merit stack.

2.2.2 Empirical Findings on Marginal vs. Average Factors

Across multiple electricity systems, empirical studies consistently show that MEF and AEF diverge substantially, and that the divergence is both temporally and spatially structured. Hawkes' analysis of the UK, US, and Australian systems found that MEF exceeded AEF by 30–50% during peak demand hours, with patterns systematic enough to support predictive modelling [15]. From an operational standpoint this is consequential: shedding one megawatt of load during a peak period delivers up to 50% more emission reduction than an AEF-based calculation would suggest.

Siler-Evans et al. [16] extended this work using instrumental variables econometrics applied to six years of US balancing authority data, addressing the endogeneity between demand and generation mix. Their estimates placed regional MEF values between 0.55 and 1.10 kg CO_2/kWh, with marginal factors running 15–35% above average factors. The resulting heterogeneity both across regions and across hours of the day means the emission value of any given shedding event can vary by up to a factor of two depending on when and where it occurs. This finding is the strongest available argument for geographically and temporally differentiated carbon-aware shedding protocols.

Ryan et al. [17] compared six MEF calculation methods across 13 US grid regions, evaluating accuracy, data requirements, and computational feasibility. Their central conclusion that marginal methods are categorically superior to average methods for demand side interventions such as load shedding provides direct methodological guidance for carbon aware operational framework design. Hourly resolution, which their analysis recommends, is straightforwardly achievable within MATLAB/Simulink environments.

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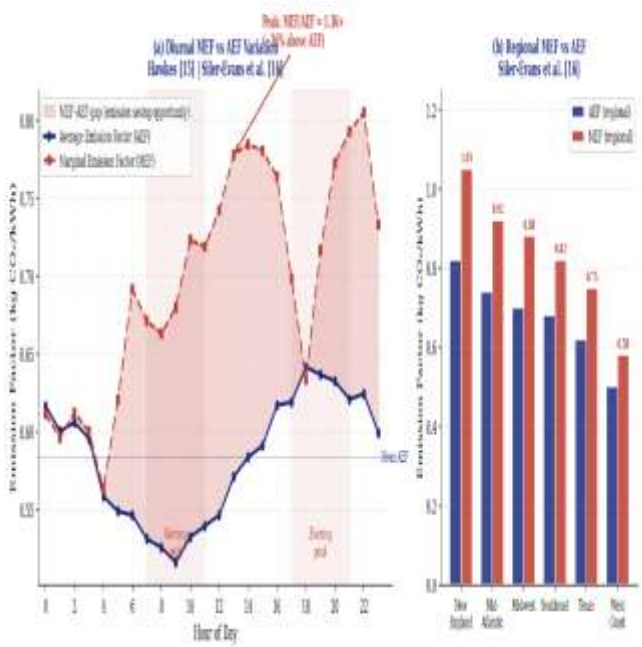

Fig.3: (a) Diurnal variation in marginal (MEF) and average (AEF) emission factors (MEF 30-50% over AEF at peak). (b) Regional MEF and AEF across US grid region, carbon aware load shedding must be MEF based to capture true emission savings of events.

2.2.3 Impact of Renewables on Marginal Emissions

Variable renewable energy penetration complicates marginal emission estimation while simultaneously creating new opportunities for emission reduction. Zhou and Wang [18] extended MEF methodology to incorporate renewable intermittency, using five minute dispatch data from the Australian National Electricity Market to train machine learning prediction models that achieved 92% real-time accuracy. Their analysis revealed that solar PV displaces higher-carbon marginal generation more effectively than wind during peak hours (0.4 vs. 0.3 kg CO_2/kWh), a consequence of the temporal alignment between solar output and peak demand.

Troy et al. [19] examined the emission consequences of wind-induced base-load cycling in Ireland's power system using unit commitment models with explicit wind uncertainty and emission constraints. Their results identified an 18% emission reduction achievable through optimized cycling, alongside a 23% reduction in cycling related emissions through emission sensitive dispatch scheduling. The broader lesson is that operational strategy not generation mix alone is a genuine and quantifiable lever for emission reduction, even in systems with high renewable penetration.

2.3 Emission Modelling Approaches

2.3.1 Carbon Emission Flow Models

Carbon emission flow theory, introduced in Section 2.1.1, remains the most computationally efficient and theoretically coherent approach to dynamic emission modelling in power networks. Yang et al. [11] extended the original formulation to incorporate transmission losses and heterogeneous generation types, using graph theory and linear programming for large-scale implementation. The emission flow on branch i–j is:

$$R_{ij} = \rho_i \cdot P_{ij} \tag{6}$$

Where R_{ij} is the emission flow on branch i–j (kg CO_2/h), ρ_i is the carbon intensity at bus i (kg CO_2/MWh), and P_{ij} is the power flow on that branch (MW). Nodal carbon intensities are obtained by solving the following system:

$$\rho_i = \frac{\left(\sum_{j \in \Pi^{I}} \rho_j \cdot P_{ji} + \sum_{g \in r^{I}} e_g \cdot P_g\right)}{\left(\sum_{j \in \Pi^{I}} P_{ji} + \sum_{g \in r^{I}} P_g\right)} \tag{7}$$

Here r_i denotes the set of generators connected to bus i, and e_g is the emission intensity of generator g [11]. This extended model achieves a 40% reduction in computational time with 97% allocation accuracy on 118-bus test systems, confirming its suitability for real-time applications at distribution scale.

2.4 Load Shedding Strategies

2.4.1 Conventional Load Shedding

Conventional under-frequency load shedding (UFLS) operates on fixed, pre-calculated relay settings derived from offline system studies. Anderson and Mirheydar [24] established the foundational methodology, in which the load shed at stage k is given by:

$$\Delta P_{L,k} = \left(\frac{2H_{sys}}{f_0}\right) \cdot \left(\frac{df}{dt}\right) \cdot \Delta t_k \tag{8}$$

Where H_{sys} is the system inertia constant, f_0 is nominal frequency, df/dt is the measured rate of frequency change, and Δt_k is the time delay at stage k. In practice, conventional schemes apply fixed values of $\Delta P_{L,k}$ regardless of how severe the actual disturbance turns out to be. This leads to systematic over-shedding for minor events and under-shedding for severe ones [24].

Despite these well-known limitations, conventional schemes remain the dominant approach across existing installations. Shah et al. [25] reviewed 45 deployed load shedding schemes and found that, while adaptive and intelligent alternatives deliver 28–42% improvements in performance metrics, conventional designs persist by virtue of their simplicity, regulatory familiarity, and low implementation cost. That installed base constitutes both a challenge and an opportunity: as ageing conventional schemes are eventually upgraded, each replacement is a candidate entry point for carbon-aware redesign.

2.4.2 Adaptive Load Shedding

Adaptive UFLS schemes overcome the fixed-setting limitation by adjusting shedding quantities and locations in real time. Terzija [26] developed an adaptive approach based on rate-of-change-of-frequency (ROCOF) measurements that estimates the generation deficit immediately after a disturbance:

$$\Delta P_{deficit} = \left(\frac{2H_{sys}}{f_0}\right) \cdot \left(\frac{df}{dt}\right) |_{t=0+} \qquad (9)$$

Where the subscript $|t=0+$ denotes the initial post-disturbance rate of frequency change. The total shed load is then set equal to the estimated deficit, with geographic distribution determined by staged thresholds and time delays. Terzija's scheme achieved 95% disturbance estimation accuracy within 200 ms, reducing total shed load by 25% while maintaining identical frequency nadir protection relative to conventional fixed-threshold schemes [26]. That efficiency gain can be directly repurposed in a carbon-aware extension: instead of simply minimizing total shed load, the scheme can preferentially shed the highest-carbon load within the deficit constraint.

Abdelaziz et al. [27] extended adaptive shedding to systems with significant renewable penetration, incorporating wide-area measurements and voltage stability indices into the shedding decision. Their approach reduced shed load by 35% relative to conventional UFLS while holding voltage within 0.95–1.05 pu under 85% renewable penetration scenarios directly relevant to the distribution network context in which carbon-aware control offers the greatest emission benefit.

2.4.3 Intelligent Load Shedding

Intelligent load shedding draws on machine learning, fuzzy inference, and formal optimization to achieve multi-objective performance. Bevrani and Hiyama [28] developed a framework incorporating fuzzy logic and neural networks, formulating the shedding decision as:

$$min[\Omega_1\Delta f(t), \Omega_2\Delta V(t), \Omega_3\Delta P_{shed}, \Omega_4\Delta E] \qquad (10)$$

Subject to nodal power balance, frequency bounds $fmin \leq f(t) \leq fmax$, and voltage bounds $Vmin \leq Vi(t) \leq Vmax$ for all buses i. Here ΔE represents the incremental emission arising from the disturbance and the shedding response, while $\Omega 1$–$\Omega 4$ are weighting coefficients [28]. The explicit inclusion of ΔE as an objective variable is a direct precursor to carbon-aware load shedding: it places emission reduction within the same decision framework as frequency and voltage recovery, rather than treating it as an afterthought. Bevrani and Hiyama validated the scheme against measurement errors and communication delays on 39-bus test system simulations, confirming practical viability under realistic operating conditions.

2.4.4 Voltage Stability-Based Load Shedding

While under-frequency load shedding targets frequency decline, under-voltage load shedding (UVLS) addresses voltage collapse a distinct but related stability concern. Muttaqi et al. [29] developed a coordinated multi-agent framework using consensus algorithms for distributed reactive power management, achieving an 82% reduction in voltage violations, a 60% decrease in transformer tap operations, and 15% energy loss savings through optimized reactive dispatch.

The relevance of UVLS to carbon-aware operation lies primarily in event prevention. Voltage instability events that cascade into uncontrolled system separation produce large, abrupt emission spikes as generators are tripped and subsequently restarted under uncoordinated conditions. Effective UVLS, by preventing such events, therefore delivers emission management benefits that extend beyond what targeted load shedding can achieve on its own.

2.4.5 Optimisation of Shedding Location

Where shedding occurs matters as much as how much is shed. Zhou and Pierre [30] used sensitivity analysis and eigenvector computation on a 179-bus test system to show that optimal location selection reduces required load drop by 30% while maintaining frequency within 59.5–60.5 Hz across 98% of contingency scenarios.

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The carbon-aware extension of this location problem can be written as:

$$i* = arg\ max_i \left[\frac{\partial \Delta f_{min}}{\partial \Delta P_{L,i}}\right] \cdot \left(\frac{1}{\rho_i}\right) \quad (11)$$

Where f_{min} is the minimum post-disturbance frequency, $\Delta P_{L,i}$ is the load shed at bus i, and ρ_i is the nodal carbon intensity at bus i [30]. This formulation explicitly trades off frequency recovery effectiveness against emission impact, selecting the shedding location that delivers the greatest frequency benefit per unit of avoided CO_2.

2.4.6 Load Shedding in Distribution Networks with Distributed Generation

Laghari et al. [7] reviewed load shedding schemes specifically for distribution networks with distributed generation (DG), identifying five characteristics that distinguish this context from transmission-level shedding: (i) lower inertia constants, which compress the available response window; (ii) heightened voltage sensitivity to power injections; (iii) variability in DG output; (iv) islanding capability, which demands autonomous protection logic; and (v) communication constraints that limit real-time coordination across dispersed assets. Taken together, these characteristics make a strong case for developing distribution specific carbon aware shedding strategies that account for both the operational constraints and the distinctive emission reduction opportunities that distribution networks present.

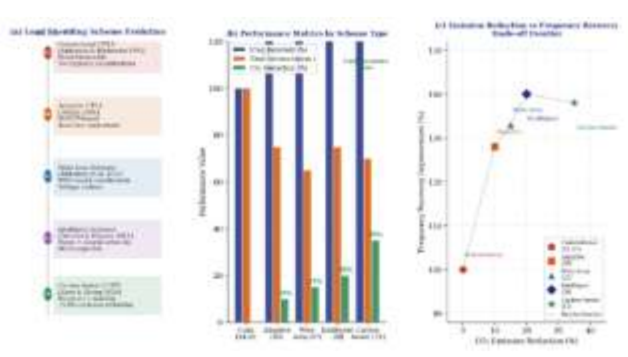

Fig 4: Load shedding scheme evolution and comparative performance. (a) Developmental timeline from conventional to carbon aware, (b) Performance metrics of high frequency recovery, (c) pareto trade off showing carbon aware load shedding the optimal frontier.

2.5 Stability Constraints on Load Shedding

2.5.1 Frequency Stability in Low-Inertia Systems

The ongoing displacement of synchronous generation by inverter-interfaced renewables is steadily reducing the inertia available to resist frequency deviations following generation loss. Xu and Dong [32] reviewed more than 150 studies on power system stability under renewable integration and identified reduced inertia as the primary emerging stability challenge, requiring 40–60% faster protective control response than conventional schemes provide. The rate of frequency change following a generation loss ΔP is:

$$\frac{df}{dt} = \Delta P \cdot \frac{f_0}{(2H_{sys})} \quad (12)$$

As H_{sys} decreases with renewable penetration, df/dt grows proportionally, tightening the window within which a load shedding response must act. Any carbon-aware shedding algorithm must therefore operate within a computational envelope that shrinks as the grid decarbonizes a direct and non-trivial constraint on the complexity of real-time carbon-optimized decision-making.

2.5.2 Voltage Stability with Distributed Generation

Tamimi et al. [33] performed dynamic stability simulations of Ontario's power system under varying solar penetration levels, identifying a voltage stability ceiling of approximately 30% solar penetration without supplementary reactive power support. Deploying STATCOM or SVC raises this ceiling to 45% while maintaining adequate stability margins. The study's practical implication for carbon-aware shedding is clear: distribution networks with high DG penetration are inherently voltage sensitive, and any shedding operation that shifts real power flows at individual buses will perturb reactive power balance and

Voltage profiles. Voltage stability margins must therefore appear as hard constraints inside the carbon-aware optimization not as secondary checks applied after the fact.

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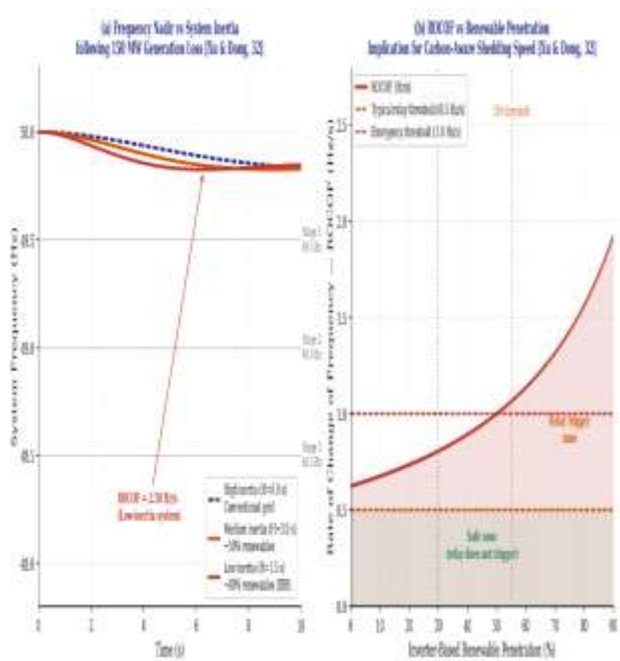

Fig 5: Frequency stability constraints in load shedding. (a) Simulated freq. nadir under three inertia levels for 150MW generation loss, low inertia requires faster shedding. (b) Increase in ROCOF with renewable integration showing that carbon aware algorithm must operate within tighter decision windows as the grid decarbonizes.

2.6 Smart Grid and ICT-Based Integration

Deploying carbon-aware load shedding in practice requires communication and sensing infrastructure that many conventional distribution networks do not yet possess. Gungor et al. [36] surveyed smart grid communication technologies, evaluating candidate protocols against the latency, bandwidth, and reliability requirements of distribution automation. Their analysis confirmed that advanced metering infrastructure (AMI) and SCADA-integrated platforms can satisfy the latency requirements for real-time carbon-aware control, provided appropriate network architecture is in place.

Fang et al. [37] characterized the four layer smart grid architecture physical, communication, data, and application and identified the data and application layers as the critical enablers of carbon-aware control: specifically, their capacity to integrate real-time carbon intensity signals with automated load management systems. Full smart grid deployment, their analysis suggested, could reduce system-wide emissions by 15–20% through demand-side optimization alone, independent of any supply-side changes.

On the demand response side, Siano [38] found that time-of-use pricing and direct load control programs could achieve 30% reductions in peak carbon emissions by shifting consumption away from high-carbon generation periods. Pepermans et al. [39] identified prosumer flexibility as a significant and underexploited carbon reduction resource, while Lund and Mathiesen [40] extended the analysis to scenarios of 100% renewable energy supply, demonstrating that distributed generation combined with demand flexibility constitutes a technically feasible pathway to net zero distribution network operation provided that coordinating control frameworks of the type outlined in Section 3 are available.

Fig.6: Layered ICT architecture for real-time carbon-aware load shedding deployment on distribution networks. Communication layer: Gungor et al. [36], Fang et al. [37]. Demand response layer: Siano [38], Pepermans et al. [39]. Physical/DG layer: Lund & Mathiesen [40]. The Control layer implements the C-OPF and intelligent shedding algorithms reviewed in 2.4.

2.7 The IEEE 33-Bus Distribution System as Validation Benchmark

Choosing the right test network for carbon-aware shedding research is consequential. The system must be complex enough to expose real operational trade-offs, yet tractable enough to permit simulation-based optimization studies. The IEEE 33-bus radial distribution system, characterized by Sumanpreet and Bala [46], has become the de facto benchmark for distribution network research involving distributed generation and demand management.

Its appeal for carbon-aware shedding research is straightforward. The radial topology is representative of real distribution feeders, published per unit parameters and load data are freely reproducible, the MATLAB/Simulink implementation is publicly available [47], and the 33-bus scale is computationally tractable for optimization-based shedding algorithms that must evaluate nodal carbon intensities in real time. Prior studies have validated the system's suitability for high-renewable-penetration studies [46], voltage stability analysis [33], and demand response optimization [38] the three most important contextual factors for carbon-aware load shedding.

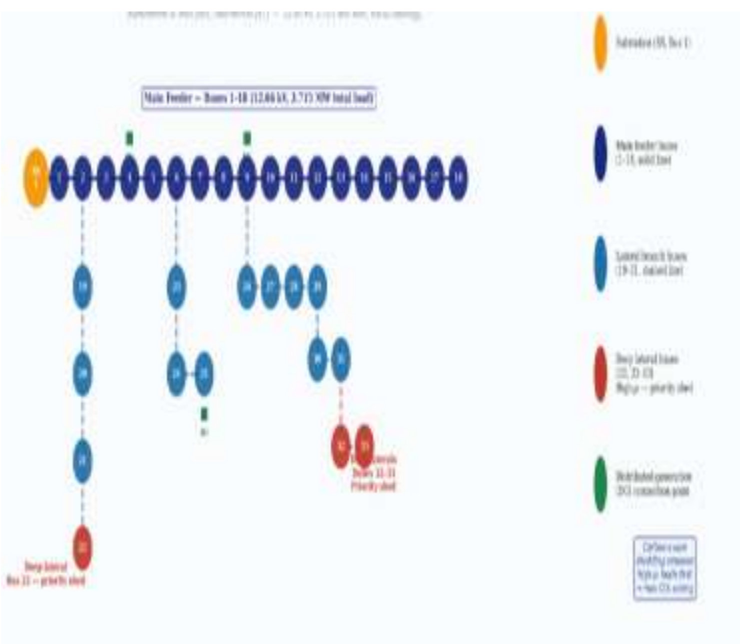

Fig: 7 Simplified topology of the IEEE 33-Bus radial distribution system selected as a defined benchmark, highlighting main feeder (buses 1-18), lateral branch buses (buses 19-31), deep lateral buses (buses 22, 32, 33) as priority shedding candidates. Mat Lab/Simulink implementation via [46, 47]

III. Synthesis and Research Agenda

3.1 Synthesis of Key Findings

The 38 studies reviewed papers here converge on a coherent set of findings with direct implications for the development of carbon-aware load shedding.

Theoretical foundation: Carbon emission flow theory [10, 11] is the most rigorous and computationally efficient framework for dynamic emission allocation in distribution networks, achieving 97% accuracy with 40% computational savings. It is the necessary theoretical infrastructure for any real-time carbon-aware operational strategy.

Marginal versus average emissions: MEF consistently exceeds AEF by 30–50% during peak periods across multiple systems [15–18]. Carbon-aware load shedding must therefore use MEF based rather than AEF based emission signals; shedding timed and located according to marginal factors delivers up to twice the emission saving of a temporally uniform approach.

Load shedding evolution: The progression from conventional fixed threshold schemes to adaptive ROCOF based and intelligent multi-objective formulations [24–28] demonstrates both the technical maturity of advanced approaches and a clear development pathway for incorporating carbon objectives within the same multi-objective optimization framework.

Stability constraints: Frequency and voltage stability requirements are non-negotiable bounds on any shedding strategy [31–35]. These constraints define the feasible space within which carbon optimization must operate; an algorithm that violates them will not survive regulatory scrutiny regardless of its emission performance.

Smart grid enablers: The ICT infrastructure reviewed in Section 2.6 [36–40] provides the communication latency, carbon intensity signal access, and demand response coordination needed to deploy real-time carbon-aware shedding on distribution networks. The barriers to deployment are increasingly organizational and regulatory rather than purely technological.

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3.2 Research Gaps and Future Directions

Four specific gaps emerge from the synthesis above, each constituting a concrete agenda item for future research.

Gap 1: No integrated carbon-aware load shedding framework for distribution networks: None of the 38 reviewed studies combines carbon emission flow theory with real-time carbon-aware load shedding in a distribution network context. The C-OPF formulations reviewed in Section 2.1.2 were developed for transmission systems and have not been adapted to distribution-specific constraints lower inertia, bidirectional power flows, and voltage sensitivity. This absence is the central research gap.

Gap 2: No real-time MEF prediction for shedding decisions: Existing MEF calculation methods are primarily retrospective [15–18]. Real-time carbon aware shedding requires predictive MEF values specifically, forecasts of which generators will be at the margin over the next shedding decision interval. LSTM architectures trained on historical dispatch and renewable output data offer a tractable path toward this capability, but have not yet been applied specifically to distribution level load shedding.

Gap 3: No life-cycle emission accounting in shedding optimization: All reviewed studies restrict emission accounting to operational stack emissions. Life cycle emissions including embodied carbon in generation infrastructure and transmission assets are systematically excluded. For systems with high renewable penetration, where operational emissions are low but embodied emissions are significant, this omission may materially bias shedding decisions.

Gap 4: No validation on realistic distribution network topologies: Intelligent and carbon-aware shedding algorithms have been validated exclusively on transmission scale test systems. The IEEE 33-bus distribution system identified in Section 2.7 is the appropriate benchmark for distribution specific validation. Future work should implement and evaluate carbon-aware shedding algorithms on this test bed in MATLAB/Simulink, enabling direct comparison with the existing literature.

IV. CONCLUSION

This review has examined 38 studies spanning carbon emission theory, emission modelling, load shedding methodologies, stability analysis, and smart grid integration to build the theoretical and empirical foundations for carbon-aware load shedding in power distribution networks.

The central finding is that all the necessary components exist, from carbon emission flow theory, marginal emission factor analysis, and multi-objective intelligent shedding formulations but they have never been assembled into an integrated framework adapted to distribution network constraints.

The evidence that MEF diverges substantially from AEF during peak periods establishes that load shedding carries significantly greater emission reduction potential than average factor analyses suggest. The evolution of shedding schemes toward multi objective intelligent architectures shows that emission objectives can and should be embedded within the same optimization framework as frequency and voltage recovery. And the smart grid infrastructure reviewed in Section 2.6 confirms that the communication and sensing prerequisites for real-time carbon-aware control are technically achievable on modern distribution networks.

The principal contribution of this review is the identification of a specific, actionable research agenda: developing and validating, on the IEEE 33-bus distribution system, a carbon-aware load shedding algorithm that integrates real-time marginal emission factor signals with multi objective stability optimization. This will require advances in predictive MEF modelling, distribution adapted C-OPF formulation, and life cycle emission accounting. The present review supplies the consolidated literature base from which that work can confidently proceed.

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