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Original Research Article

Intelligent voltage sag management in smat grids: A review of machine learing predicion and cooperative control techniques

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Abstract: Voltage sags are critical power quality disturbances in modern smart grids, worsened by renewable energy integration and distributed generation. Traditional physics-based methods fail to handle high-dimensional data and non-linear dynamics, prompting the adoption of machine learning (ML) for prediction and multi-agent reinforcement learning (MARL) for cooperative control. This review synthesizes key advances in ML (traditional techniques and deep learning) for sag detection/classification, and MARL (via the CTDE paradigm) for distributed voltage regulation. Critical gaps—Rigid architectures, deployment barriers, lack of benchmarks—are identified, with pathways to unify prediction and control. It provides a foundation for advancing intelligent sag management in smart grids.

Keywords: voltage sag management; smart grids; machine learning; multi-agent reinforcement learning (MARL); CTDE paradigm; deep learning

1. Introduction

Voltage sags—Short-duration (0.5–300 cycles) voltage reductions (10–90% of nominal value)—Disrupt industrial processes and critical infrastructure, causing substantial economic losses[1]. For instance, a single voltage sag event can force a manufacturing plant's assembly line to shut down for hours, resulting in tens of thousands of dollars in lost productivity; in healthcare settings, it may interrupt life-support equipment or diagnostic systems, posing direct risks to patient safety[2]. Even in commercial buildings, sags can disrupt data centers or HVAC systems, leading to service outages that erode customer trust. Despite their relatively low frequency (typically tens of events per year per regional grid), their wide-ranging impact makes effective sag management a top priority for grid operators.

Traditional analysis of voltage sags relies on physics-based methods such as the Method of Fault Positions and Voltage Divider Model. These approaches are theoretically rigorous and work well for small, static grids, but they struggle to keep pace with the complexity of modern smart grids. A key limitation is their inability to process real-time high-dimensional data streams—Generated by phasor measurement units (PMUs) and smart meters at millisecond intervals—Or capture non-linear dynamics introduced by renewable energy sources (which now reach 30–65% penetration in many grids) and distributed generation (DG)[3]. When faced with parameter uncertainties (e.g., fluctuating renewable output or varying load demands), these traditional methods often experience 30–50% performance degradation, rendering them unreliable for real-time decision-making[4].

Worse still, traditional methods are inherently rigid, dependent on fixed grid topology and pre-defined system parameters. Modern grids, however, are dynamic: they frequently undergo changes like DG integration, line maintenance, or load redistribution. Adjusting traditional models to accommodate these changes requires manual reconfiguration and re-simulation, a process that can take days to weeks—Far too slow for addressing urgent sag risks[5]. Compounding this, the randomness of renewable energy output—Such as sudden drops in photovoltaic generation due to cloud cover or wind speed fluctuations—Adds unpredictable sag triggers that traditional methods cannot anticipate, leaving grids vulnerable to unplanned disturbances.

Compounding these challenges, modern smart grids leverage advanced monitoring tools—Phasor measurement units (PMUs) and smart meters—That generate millisecond-level high-frequency data streams.

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This data explosion overwhelms traditional methods, which lack the computational efficiency to process real-time information for proactive sag mitigation. Meanwhile, decentralized energy assets (rooftop PV systems, community energy storage, and microgrids) demand coordination beyond the scope of centralized control systems. A single regional grid may now host thousands of such distributed assets, each requiring real-time adjustments to avoid or mitigate voltage sags—Far more than a centralized controller can manage efficiently[6].

To address this confluence of challenges, two complementary technological approaches have emerged as game-changers: ML-based prediction and MARL-based cooperative control. ML techniques excel at processing large datasets to detect, classify, and localize voltage sags in real time, while MARL enables distributed coordination of grid assets without relying on a single central controller. This review synthesizes the key advances in both fields, identifies critical unresolved gaps, and outlines pathways to integrate prediction and control into a unified intelligent voltage sag management system—One that can adapt to the dynamic, decentralized nature of modern smart grids.

2. Machine learning for voltage sag prediction

ML enables data-driven sag analysis by leveraging large datasets to capture complex grid patterns, avoiding oversimplified models. It is split into traditional ML and deep learning (DL), each tailored to specific tasks.

2.1. Traditional machine learning approaches

Traditional ML excels in structured data processing, with Support Vector Machines (SVMs) being particularly effective for sag analysis. SVMs construct an optimal hyperplane to maximize class margins, and their kernel flexibility (linear, polynomial, RBF) captures non-linear grid dynamics. Multi-kernel SVMs, for example, achieved 95% accuracy in voltage sag source localization across Brazilian utility simulations, outperforming conventional location methods by extracting distinguishing features[7].

Other techniques like Decision Trees (DTs) offer transparent "if-then" rule-based classification, critical for operator trust, but SVMs remain preferred for rare sag events due to their robustness with limited data, the overall mechanisms is shown in **Figure1**.

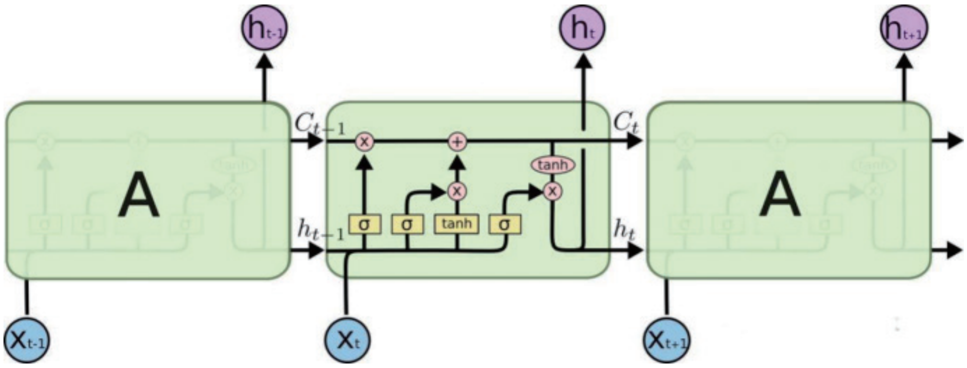

Figure 1. Architecture and operational mechanisms of systems.

2.2. Deep learning innovations

DL addresses traditional ML's limitations in handling unstructured data (e.g., raw voltage waveforms). Long Short-Term Memory (LSTM) networks, with gating mechanisms (forget, input, output), solve the vanishing gradient problem to capture temporal sag patterns. End-to-end LSTM models classified three-phase sag signals with 90.2% accuracy without manual feature engineering, a key advantage over traditional methods that require labor-intensive feature extraction[8].

DL variants like CNN-BiGRU hybrids (combining spatial and temporal modeling) and Transformers (for long-range dependencies) further improve performance, but LSTMs remain widely used for sag prediction due to their balance of accuracy and computational efficiency.

3. MARL-based cooperative control for voltage regulation

ML predicts sags, but cooperative control ensures timely mitigation. Modern grids—With thousands of

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distributed assets (PV inverters, energy storage)—Require decentralized coordination, which MARL enables by solving two core challenges: non-stationarity (dynamic agent policies altering the environment) and credit assignment (attributing global rewards to individuals).

3.1. The CTDE paradigm

Centralized Training with Decentralized Execution (CTDE) is the backbone of MARL for grids. During training, a central critic uses global data (bus voltages, power flows) to learn joint action-values, stabilizing learning by accounting for all agents' dynamics. During execution, agents make decisions via local observations (e.g., a PV inverter using its bus voltage), aligning with real-world grid constraints[5]. This reduces communication overhead and ensures scalability.

3.2. Representative MARL algorithms & applications

QMIX, a key MARL algorithm, uses monotonic value decomposition to align individual agent utilities with global rewards, solving credit assignment. For distributed energy storage coordination, QMIX improved storage utilization from 60% to 85% while keeping State of Charge (SOC) within a healthy 20–80% range, avoiding battery degradation[6].

In voltage control, multi-timescale MARL (fast inverter control, slow OLTC adjustment) achieved 98.5% voltage compliance and kept bus voltage fluctuations within ±0.03 p.u., demonstrating its ability to handle dynamic grid conditions[7]. Other algorithms like MADDPG (for inverter coordination) and MAPPO (for safety-critical settings) further validate MARL's efficacy, but QMIX stands out for balancing performance and practicality.

4. Challenges and future directions

Four critical gaps hinder full deployment:

Architectural Rigidity: Fixed-resolution signal processing and monolithic ML models fail to adapt to multi-scale dynamics (e.g., millisecond sags vs. hourly load patterns).

Deployment Barriers: High computational costs, inference latency (50–100ms vs. <10ms grid needs), and communication delays (causing 20–40% performance loss) limit real-world use [8].

Lack of Benchmarks: No standardized datasets or metrics, making cross-study comparisons impossible; models degrade by 30–50% with renewable penetration shifts [9].

Edge Deployment Limits: Large DL/MARL models require resource-constrained edge devices (e.g., RTUs) to be compressed (35–49× size reduction) [10].

Future research should: (1) Develop multi-agent prediction architectures (e.g., embedding MARL's "division of labor" into ML models); (2) Optimize edge deployment via compression; (3) Establish unified validation frameworks linking prediction accuracy to control performance.

Illustration: CTDE Paradigm for MARL-Based Voltage Control

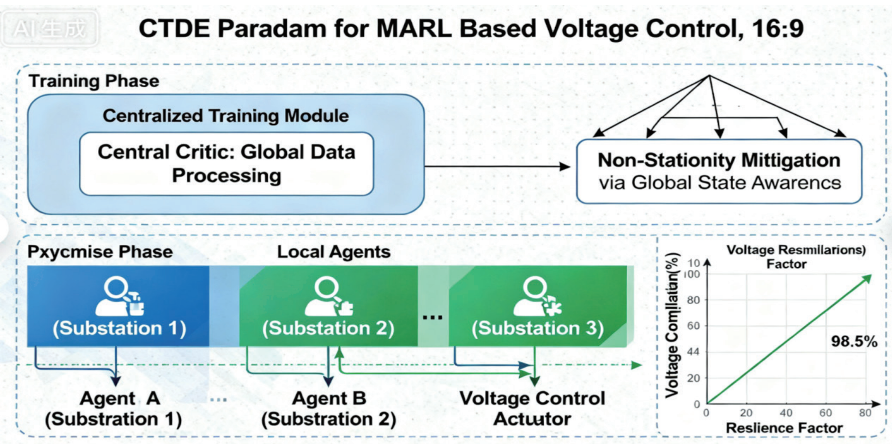

Figure 2. CTDE decouples training (central critic uses global data to address non-stationarity) and execution (local agents act on local observations). This structure enables 98.5% voltage compliance while maintaining grid resilience [9,10].

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