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Smart Grids

Innovations for a Sustainable Future

Edited by Ahmed F. Zobaa



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Meet the editor



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Preface

Smart grids are undergoing a profound transformation as power systems evolve toward decarbonization, decentralization, and digitalization. The increasing penetration of renewable energy sources, the widespread deployment of power electronic interfaces, and the growing reliance on data-driven intelligence are fundamentally reshaping how electricity systems are planned, operated, and governed. In this context, smart grids are no longer defined solely by advanced sensing and communication infrastructures, but by their ability to integrate artificial intelligence, ensure cyber-physical security, enable flexible market participation, and deliver tangible social and environmental benefits. This edited volume, *Smart Grids – Innovations for a Sustainable Future*, brings together contemporary research and applied perspectives that collectively address these emerging challenges and opportunities.

The primary objective of this book is to provide a coherent and multidisciplinary overview of innovative approaches that support the development of sustainable, resilient, and intelligent smart grids. Rather than presenting isolated technical advances, the volume emphasizes the interconnection between sustainability, trustworthy artificial intelligence, advanced control of microgrids, cybersecurity, market and policy frameworks, and community-oriented applications. The chapters are written by leading researchers and practitioners and are intended for a broad readership, including academics, graduate students, engineers, system operators, policymakers, and stakeholders involved in the energy transition.

The volume opens with foundational perspectives on sustainability and trust in intelligent energy systems. The first chapter, *Perspective Chapter: Envisioning Sustainable AI with Decentralized Granular Certificates – DeGCert*, introduces a novel framework for ensuring verifiable, time-resolved renewable energy use in artificial intelligence operations through decentralized granular certificates. By combining blockchain technologies with energy attribute certification, the chapter highlights how transparency and traceability can support truly carbon-free digital infrastructures. Building on this foundation, the second chapter, *Trustworthy AI in Smart Grid Systems*, examines ethical principles of artificial intelligence, fairness, explainability, and accountability in critical energy infrastructure. It discusses how trustworthy AI practices are essential for public acceptance, regulatory compliance, and long-term reliability of AI-driven smart grid applications.

The book then transitions to data-driven intelligence as an operational enabler of smart grids. The third chapter, *Machine Learning-Driven Stacked Ensemble Meta-Learning for Short-Term Solar Power Forecasting*, presents advanced ensemble learning techniques designed to improve the accuracy and robustness of short-term

photovoltaic power forecasting. Accurate forecasting is a critical prerequisite for efficient renewable integration, grid reliability, and informed operational decision-making in modern power systems.

Advanced control and power management of microgrids form the core technical focus of the subsequent section. The fourth chapter, *Advanced Power Management in Renewable Energy Microgrids*, provides a comprehensive treatment of power management challenges in both grid-connected and islanded microgrids. It discusses issues such as power sharing, inertia emulation, voltage regulation, and the coordination of multiple control objectives, while also outlining future trends involving digital twins and artificial intelligence. Complementing this perspective, the fifth chapter, *Advanced Multi-Agent Reinforcement Learning Strategy for Power Regulation in Standalone Microgrids*, introduces a fully decentralized, model-free control framework based on multi-agent deep reinforcement learning. The chapter demonstrates how autonomous inverter-based resources can learn optimal control strategies to enhance stability, resilience, and power-sharing accuracy without reliance on centralized communication or detailed system models.

As smart grids become increasingly digital and interconnected, cyber-physical security and operational integrity emerge as critical concerns. The sixth chapter, *Anomaly Detection and State Estimation Integrity Preservation in the Smart Grid*, addresses these challenges by presenting lightweight statistical methods for detecting anomalies and mitigating false-data-injection attacks. Focusing on wide-area monitoring systems and state estimation, the chapter highlights practical approaches for preserving situational awareness and ensuring robust grid operation under adverse conditions.

The system-level enablement of smart grids through economic and regulatory mechanisms is addressed in the seventh chapter, *Market Mechanisms and Policy Frameworks for Enabling Smart Grids in the Energy Transition*. This chapter provides a policy-oriented analysis of electricity market design, ancillary services, and regulatory coordination required to support large-scale renewable integration and system flexibility. It emphasizes that technical innovation must be accompanied by aligned market structures and policy frameworks to enable sustainable, scalable deployment.

The volume concludes with a community-centered and socio-technical perspective. The eighth chapter, *Small Productive Processes in Microgrids: Opportunities and Challenges for Sustainable Development of Communities*, explores how microgrids can support rural and local development through participatory design and integration with small productive processes. By adopting a socio-technical and co-construction methodology, the chapter illustrates how smart grid technologies can contribute not only to energy sustainability but also to social inclusion, local capacity building, and long-term community resilience.

Taken together, the chapters in this book offer a holistic view of smart grid innovation, spanning from foundational concepts of sustainability and trustworthy artificial intelligence to advanced control, security, markets, and societal impact. While each chapter addresses a distinct aspect of the smart grid ecosystem, their collective contribution underscores a central message: the future of smart grids depends on the thoughtful integration of technology, governance, and human-centered design.

The Academic Editor would like to acknowledge the valuable contributions of all chapter authors for their commitment, expertise, and timely cooperation throughout the editorial process. Appreciation is also extended to the publishing team for their professional guidance and support during the development of this volume.

This book will serve as a useful reference and inspiration for researchers and practitioners working toward the realization of intelligent, secure, and sustainable power systems.

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Section 1

Foundations for Sustainable and Intelligent Smart Grids

Perspective Chapter: Envisioning Sustainable AI with Decentralized Granular Certificates – DeGCert

Saqib Rasool and Rune Hylsberg Jacobsen

Abstract

The global rise of AI is driving a surge in electricity demand, with massive foundation models (e.g., GPT-4, Google's Gemini) consuming unprecedented amounts of energy and contributing to increased carbon emissions. We must make urgent efforts to decarbonize AI's power-hungry growth to meet our climate goals. This chapter proposes blockchain-based Decentralized Granular Certificates (DeGCert) to ensure verifiable, 24/7 renewable energy use in AI training and operations on decentralized blockchain platforms. We qualitatively compare current blockchain AI projects and illustrate how conventional Granular Certificates versus our DeGCert framework perform in achieving sustainable AI. Integrating fine-grained energy certificates directly into blockchain ecosystems enhances transparency, traceability, and trust. DeGCert emerges as a foundational mechanism to achieve verifiable, 24/7 carbon-free AI, enabling the development of provable, renewable-powered models and establishing a pathway toward truly transparent, sustainable AI.

Keywords: sustainable AI, decentralized granular certificates, DeGCert, granular certificates, energy attribute certificates, 24/7 carbon-free energy, carbon-aware scheduling, renewable-powered compute

1. Introduction

Artificial intelligence systems have experienced tremendous growth in scale and capability. Modern foundation models, such as OpenAI's GPT-4 and Google DeepMind's Gemini, are pushing the boundaries of compute, data, and model size. This rapid progress comes with an exponential increase in energy consumption and carbon emissions [1]. Large-scale training runs require a substantial amount of electricity, contributing significantly to AI's carbon footprint. Globally, data centers (increasingly AI-driven) consumed roughly 1–2% of all electricity as of the mid-2020s [2, 3] and this share is projected to be doubled by 2030, driven largely by AI workloads [4]. In the United States, for example, AI-related data centers are projected to consume more power by 2030 than the nation's manufacturing industry for some heavy materials [4]. The unsustainable energy appetite of AI is raising

alarms that unchecked growth could undermine the climate targets [2]. Researchers and analysts have warned that the expansion of AI data centers, if powered by fossil-heavy grids, may “overwhelm” and “undermine” both national and corporate net-zero commitments [2]. This soaring energy demand calls for innovative decarbonization strategies to ensure AI’s progress does not come at the expense of the planet’s health.

To achieve sustainable AI, transitioning AI’s energy supply to renewable sources is imperative. In practice, this means powering compute-intensive training and inference with solar, wind, hydro, and other clean energy. A promising approach is to tap into prosumer-generated surplus green energy, like electricity from residential solar panels or community wind farms that might otherwise be curtailed or sold at a low price. Rather than letting renewable generation go to waste during off-peak demand, we can redirect this excess energy to AI workloads. For example, one data center startup reports that 30–40% of potential wind and solar output can go unused due to transmission limits or timing mismatches [5]. In 2021, an estimated 14.9 TWh of renewable electricity went unused—enough to power 1.3 million households for a year and representing about \$610 million in lost revenue—revealing a significant opportunity to harness this “stranded” green power for computing tasks [5]. Since then, curtailment levels have continued to rise; for instance, in 2025, the grid operator for most of California curtailed 3.4 million MWh of utility-scale wind and solar output, marking a 29 percent increase compared with 2023. In California, these curtailments have resulted mainly from transmission bottlenecks and demand imbalances, underscoring the persistent challenge of integrating variable renewables into the grid [5].

By scheduling AI training jobs to run when rooftop solar is overproducing or when nighttime winds are strong, AI developers can directly consume locally generated clean power. This strategy not only reduces emissions but also enhances the economics of renewable projects by providing flexible demand. Crucially, however, sustainable AI requires verifiable mechanisms to prove that the renewable energy actually powers it. It is not enough to simply say an AI model was “green-powered,” and there must be auditable proof of the renewable origin of the electricity at each step. A blockchain-based decentralized system offers a way to add transparency to the system by eliminating the need to trust a single entity unquestioningly.

Blockchain-based decentralized computing platforms are emerging that distribute AI workloads across many nodes and reward contributors with cryptocurrency. Projects such as Golem and iExec have pioneered peer-to-peer cloud marketplaces on Ethereum, allowing users to rent out CPU/GPU power and get paid in tokens [6]. Newer networks like DeepBrain Chain (a GPU computing blockchain on NEO), Akash Network (a decentralized cloud on Cosmos), Render Network (for distributed GPU rendering and AI tasks), and NodeAI (a decentralized GPU platform) similarly incentivize globally distributed hardware to run AI workloads [7, 8]. These systems aim to democratize access to computing by utilizing idle resources, with cryptographic payments ensuring fair compensation for the resources used. However, one glaring gap is that none of these platforms provides transparency about the energy source powering the computations. A provider on Golem or Render might be using coal-based electricity. Yet, there is currently no way for the system (or the task requester) to know or verify the carbon intensity of the contributed compute. Thus, while decentralized AI platforms address the distribution of computation, they do not inherently guarantee sustainability or the use of renewable energy.

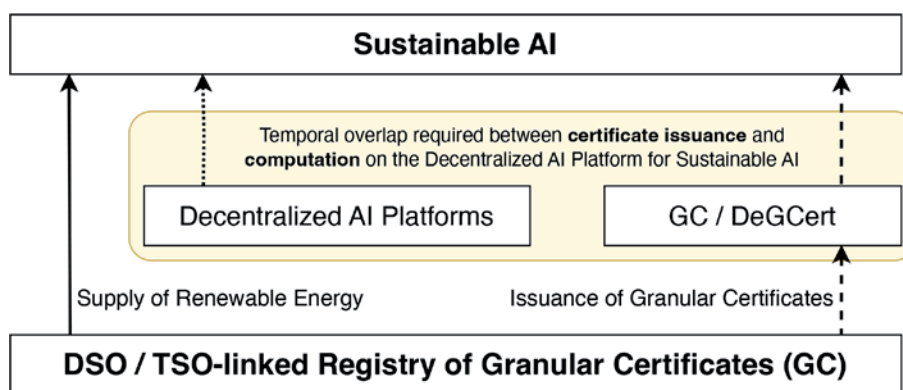


Figure 1.
 Workflow for achieving sustainable AI computation on decentralized AI platforms through GC/DeGCerts.

Figure 1 illustrates a typical workflow of the sustainable AI solution, where the registry issues Granular Certificates (GCs) only when renewable sources supply the energy. Users verify the sustainable AI operations by matching the time of certificate issuance with the period of computation on the decentralized AI platform. In this chapter, we introduce Decentralized Granular Certificates (DeGCert) as a novel mechanism that enables verifiable tracking of renewable energy within decentralized AI systems. A DeGCert records, on a blockchain, a time-stamped digital proof showing that a producer generated a specific quantity of renewable electricity within a defined interval (e.g., a 15-minute window). As shown in **Figure 1**, both GCs and DeGCerts are interchangeable. We compare them in Section 6 to demonstrate the effectiveness of DeGCert in achieving more sustainable AI.

When we integrate DeGCert with AI compute transactions, we attach a proof of clean energy usage to every workload. This mechanism builds confidence in sustainability claims because it replaces reliance on annual averages or broad offsets with a traceable, tamper-proof record. For example, the system records that a verified solar facility supplied 500 kWh to train a model between 1 PM and 4 PM on a specific day. The ledger stores these proofs immutably, allowing any stakeholder to audit them directly. Writing these proofs to an immutable ledger means any stakeholder can audit them. In essence, DeGCerts enable AI processes to be linked with renewable energy in real time, with blockchain providing the transparency and trustlessness necessary for verification [9]. This chapter presents the DeGCert framework and outlines how it can be woven into existing decentralized AI ecosystems to create a virtuous cycle: AI drives demand for renewables, and DeGCerts prove AI's carbon-free operation.

The remainder of this chapter is organized as follows. Section 2 quantifies AI's growing energy footprint and highlights the need for sustainable AI, identifying the parts of the AI lifecycle that consume the most energy. Section 3 examines traditional energy attribute certificates (such as RECs and GOs) and their limitations, and then introduces the concept of GC with an acceptable temporal resolution. Section 4 traces the evolution from centralized AI infrastructure (as exemplified by OpenAI's 7500-node Kubernetes cluster) to decentralized, blockchain-based AI platforms. Section 5 details how granular energy certificates can be integrated into blockchain AI systems, comparing approaches such as light-client verification, oracles, cross-chain bridges, and zero-knowledge proofs. Section 6 presents

a comparative analysis of conventional GC versus our proposed DeGCert across key criteria, including transparency, scalability, and trust. Section 7 outlines future research directions from carbon-aware scheduling algorithms to new blockchain architectures purpose-built for sustainable AI. Finally, Section 8 concludes by affirming that DeGCert can enable provable renewable-powered AI, offering a higher assurance of sustainability than current practices, and it calls for broader initiatives to adopt 24/7 carbon-free standards.

2. Need and significance of sustainable AI

The energy footprint and carbon emissions of AI have escalated dramatically with the rise of large-scale machine learning. Training cutting-edge models requires enormous computational power and electrical energy. For example, a 2019 study estimated that training a single large NLP model (with hyperparameter tuning) emitted 626,000 pounds of CO₂—roughly 284 metric tons, equivalent to the lifetime emissions of five cars [10].

2.1 Escalating energy and carbon footprint of AI

More recently, OpenAI’s GPT-3 (175 billion parameters) reported to consume about 1287 MWh of electricity during training, which was enough to power 100 U.S. homes for a year, with an associated carbon footprint of 502 tCO₂ [11]. The financial cost of that single training run was on the order of \$4–5 million in cloud compute [11]. Newer models, such as GPT-4 and Google’s Gemini, are even more resource-intensive, suggesting that energy demands will continue to grow. Indeed, one analysis found the compute used in state-of-the-art AI training has been doubling every 3–4 months since 2012, far outpacing Moore’s Law [11]. While some optimists note that improved hardware and efficiency could eventually slow the growth of AI’s carbon footprint [12], current trends indicate that AI’s energy usage is racing upward. Google estimated that its data centers (many of which run AI services) used approximately 15.5 TWh in 2022, which has more power than the entire city of San Francisco requires [11]. Industry-wide, data center electricity consumption reached about 2% of global electricity in 2022 (rivaling the airline industry’s emissions) [11]. Without intervention, this trend is likely to continue escalating as AI adoption expands. We can start by identifying the high-impact phases of the AI lifecycle and decarbonizing those to prevent AI from becoming a significant contributor to emissions.

2.2 Energy distribution across the AI lifecycle

An AI system’s lifecycle spans multiple phases, each with different energy profiles. We can break down the lifecycle into the following stages: data collection, data preprocessing, model training, model fine-tuning, deployment (model hosting), and inference (serving user queries). Consider a concrete example of ChatGPT (a generative language model service based on GPT). First, large datasets are gathered (through web crawls and digitized texts) and preprocessed (cleaning and tokenizing), which can involve substantial but parallelizable computation. The core training phase then utilizes GPU/TPU clusters for weeks, consuming the bulk of energy as it iteratively adjusts billions of weights. After training the base model, OpenAI

devoted further energy to fine-tuning it for specific tasks or safety alignment through reinforcement learning. Once deployed, the model runs on servers (possibly with GPUs) to handle millions of user inferences/questions, which draws continuous power. Notably, training is often a one-time (albeit extremely energy-intensive) event for a model version, whereas inference is an ongoing process as long as users query the model. Recent estimates indicate that for popular services, the inference energy can rival or even exceed training—for example, running an AI assistant like ChatGPT for a full day to serve global users could consume as much electricity as a small country [11]. In summary, model training and large-scale inference are the most energy-hungry stages. Data preprocessing and occasional retraining or fine-tuning also contribute, but can be scheduled more flexibly; deployment energy depends on model size and usage patterns.

2.3 Leveraging energy flexibility through carbon-aware scheduling

Crucially, we can schedule some phases of AI work in a more energy-flexible way to align with renewable availability. Training jobs and data preprocessing tasks often do not require precise clock-time execution, and thus, we can put them in a queue to run when and where clean power is available. For instance, non-urgent data processing might be performed at noon when solar generation peaks, or overnight when wind farms are producing surplus electricity. Periodic model retraining or batch inference jobs (e.g., updating an AI model with new data every week) could also be timed to match renewable output. These flexible workloads present opportunities for carbon-aware scheduling—delaying or advancing computation based on the forecasted carbon intensity of the grid. Google has demonstrated this in action with experiments. Google’s carbon-intelligent platform can shift compute tasks across time (and even across data center locations) to run when more renewable energy is available on the grid [13, 14]. In one case, Google reported moving large batch workloads to early afternoon to take advantage of excess solar generation, which significantly reduced the emissions of those tasks [14]. Such load shifting does not impact the result of the computation, but it ensures they get done with cleaner power. Flexible phases, such as data preparation, model training, and hyperparameter tuning, are the prime candidates for this treatment. In contrast, real-time inference for user requests is less flexible (it must respond instantly, though even inference can be routed to regions with cleaner grids if possible).

2.4 Centralized carbon-aware scheduling and its limitations

It is essential to note that extensive academic, industrial, and open-source efforts have already focused on reducing the carbon footprint of centralized AI platforms through carbon-aware workload scheduling, energy-adaptive orchestration, and renewable-aware infrastructure management. For instance, academic schedulers such as GREEN and CausalTune have demonstrated carbon-aware machine learning clusters that align AI training with periods of low-grid carbon intensity [15, 16]. Industrial leaders, such as Google and Microsoft, have implemented carbon-intelligent schedulers within their hyperscale data centers [14, 17]. At the same time, open-source frameworks such as CNCF Kepler, Compute Gardener, and the Carbon Aware SDK have made significant progress toward declaratively managing AI workloads with sustainability policies encoded as code [18, 19]. However, all of these advancements operate under the assumption of centralized awareness of computational

resources and grid conditions. For example, Google’s system can seamlessly redirect non-urgent computation from one region to another where renewable energy is more readily available, as it maintains complete global visibility of its compute fleet and energy sources.

2.5 Challenges of decentralized AI environments

In contrast, decentralized AI platforms, which distribute computation across independent nodes owned by diverse participants, lack this unified visibility. Such platforms, often based on blockchain or peer-to-peer infrastructures (e.g., Akash Network, DeepBrain Chain, and Render Network), cannot pre-emptively access global knowledge of compute availability, location, or carbon intensity before scheduling tasks [20]. The absence of infrastructure awareness fundamentally distinguishes decentralized AI from its centralized counterparts. While centralized operators like Google can plan carbon-optimized workload migration ahead of time, decentralized networks must rely on distributed consensus and partial information, making proactive carbon-aware scheduling significantly more complex. Consequently, this study focuses exclusively on decentralized AI environments, where sustainable scheduling, energy telemetry, and certificate-based carbon accounting have yet to be adequately explored. Our proposed approach aims to extend the philosophy of carbon-aware AI scheduling to these decentralized ecosystems, thereby bridging the current gap between carbon-intelligent orchestration and trustless, distributed computing systems.

Furthermore, to verify that AI workloads are truly running on renewable electricity (and not simply claiming so while using normal grid power), we need granular energy tracking mechanisms. It is not sufficient to offset a data center’s annual consumption with a pile of renewable energy certificates (RECs)—that would be volumetric accounting with no time matching. Instead, we require fine-grained, timestamped certificates that document precisely when and where renewable energy was produced and consumed by AI. In short, achieving verifiable 24/7 carbon-free AI demands the use of granular certificates, which is the focus of Section 3.

3. From volumetric to temporal energy certificates

Most renewable energy accounting today relies on conventional energy certificates such as Renewable Energy Certificates (RECs) in North America, Guarantees of Origin (GOs) in Europe, or International Renewable Energy Certificates (I-RECs) in other regions. These certificates are the backbone of market-based accounting in the Greenhouse Gas (GHG) Protocol for Scope 2 emissions, allowing organizations to claim the use of renewable electricity. We have labeled these certificates in **Figure 2** to illustrate their evolutionary path. The first generation, consisting of these volumetric certificates, is limited by an annual matching approach that often masks the use of fossil fuels during hours when renewables are unavailable. To address this, second-generation GCs were introduced to provide finer temporal matching; however, they remain hindered by their reliance on centralized registries and the administrative burden of manual verification cycles. Hence, the focus of this section is to explain the limitations of the first two energy certificate generations, laying the foundation for our proposed third-generation energy certificates, which we have labeled DeGCert.



Figure 2.
 The evolution of certification frameworks: From I-EAC, through GC, to our proposed DeGCert.

3.1 Limitations of conventional energy certificates

Under current GHG Protocol guidelines, companies can purchase RECs or GOs equivalent to their yearly electricity consumption and thereby report those MWh as “renewable” [21]. For example, a data center consuming 100 GWh of energy in a year can purchase 100 GWh worth of certificates from wind/solar projects to offset its usage. However, this annual volumetric approach has a fundamental limitation: It does not actually map the production and consumption times of the renewable energy. A company might purchase a large bundle of solar RECs produced in the summer and use them to “green” its consumption on a winter night, when in reality the grid was fueled by fossil fuels. The GHG Protocol’s yearly matching and regional averaging allow such discrepancies [21]. It can lead to situations where an organization claims 100% renewable electricity on paper but still draws power from coal or gas plants during certain hours. In other words, conventional certificates focus on quantity (MWh) over a year, not the timing, and it is a limitation that has drawn criticism for enabling greenwashing and overstated climate claims [9].

3.2 Regional fragmentation of certificate systems

Regional fragmentation further complicates the current certificate system. RECs, GOs, and I-RECs are not globally unified; each operates in specific markets with its own registries and rules. In Europe, GOs are issued under an EU-wide framework and coordinated by the Association of Issuing Bodies (AIB), facilitating some cross-border trade of certificates within Europe [22]. Yet even within Europe, certain countries have independent schemes (for instance, the UK uses Renewable Energy Guarantees of Origin, or REGOs, which, after Brexit, are no longer interchangeable with EU GOs) [22]. North America’s RECs are administered by various regional registries (PJM-GATS, M-RETS, WREGIS, etc.), and a REC from one region is generally not recognized elsewhere [22]. I-RECs were created to extend certificate markets to countries lacking their own systems, and they cover over 50 countries in Asia, Africa, and Latin America with a standardized process [22]. However, I-RECs still function separately from RECs/GOs, and China now runs its own Green Electricity Certificate (GEC) program as the sole legal proof of renewable consumption domestically [5]. The net effect is a heterogeneous patchwork of certificate systems globally. A multinational company must navigate multiple tracking systems to certify renewable energy in each jurisdiction. This lack of a unified standard makes it difficult to perform unified, transparent verification of a claim like “our AI cloud is 100% powered by renewables,” because that claim may be backed by a mix of RECs, GOs, GECs, etc., from different markets, each with its own set of rules.

3.3 National-level differences and interoperability challenges

Differences in certificate standards at the national level underscore the challenges. As mentioned, the UK’s REGO, while similar in function to the EU GO, is now

separate. Hence, a British data center cannot directly use EU GOs to make claims, it needs REGOs (or an agreement to recognize GOs, which currently does not exist) [22]. China's GEC system, launched in 2017 and expanded nationwide by 2023, requires energy-intensive industries (including data centers) to obtain GECs, ensuring that by 2030, their renewable electricity consumption meets the national average renewable share [5]. Each Chinese GEC represents 1 MWh of green power and is tracked in a central registry, with trading platforms in Beijing and Guangzhou for unbundled certificates [5]. Yet, Chinese GECs are not fungible with I-RECs or GOs from elsewhere. Hence, a company's Chinese operations must use GECs, whereas its European operations use GOs, and so on. Thus, no single global certificate standard currently exists. The interoperability challenges mean that verifying an enterprise's renewable energy usage claim requires aggregating evidence from multiple systems, potentially leading to gaps or double-counting if not carefully managed. For AI developers deploying models across international cloud regions, it becomes non-trivial to prove each region's workloads were renewably powered under this patchwork of certificate regimes (**Figure 2**).

3.4 Granular certificates

To address the temporal and interoperability shortcomings, initiatives like EnergyTag have introduced the concept of Granular Certificates (GCs). Granular Certificates are energy certificates with fine time resolution, typically 1 hour or 15 minutes, instead of yearly aggregates. The central purpose, as defined by the EnergyTag standard, is to make electricity traceability "more closely represent physical reality and real-world availability of clean energy sources" [9]. In practice, a GC might say, "1MWh of solar power generated between 14:00–15:00 on 2025-07-21 at X location." By matching such certificates to the same time intervals of consumption, consumers can demonstrate true hour-by-hour renewable matching. EnergyTag's framework envisions certificates with timestamps and potentially geo-tags, issued *via* existing registries but following a unified standard so that an hour of wind in Germany and an hour of solar in California can both be counted toward their respective hour of load. Many national bodies are experimenting with granular certificate pilots, for instance, the European Energy Track and Trace (ETT) project with several TSOs is aligning certificate infrastructure with the EnergyTag 15-minute standard [9]. Granular Certificates greatly improve temporal accuracy: An analysis in Joule found that hourly matching can reduce emissions more effectively than annual RECs, because it sends demand signals for storage and clean energy at needed times [23]. Nonetheless, few efforts have integrated GCs into blockchain ecosystems to date [24–26]. Most granular certificate systems still rely on centralized registries and exchanges. Sections 4 and 5 will explore how decentralization (*via* blockchain) can enhance the usability of these certificates and how GCs can be embedded into decentralized AI platforms for automatic, trust-minimized sustainability tracking.

4. Blockchain-based decentralized AI platforms

Since we have already discussed the case study of ChatGPT, we are starting from the deployment of ChatGPT by OpenAI. OpenAI reportedly runs its models on large centralized clusters—in one report, OpenAI engineers described scaling a Kubernetes cluster to 7500 nodes (spanning tens of thousands of GPUs) to train models like GPT-3, CLIP, and DALL·E [27].

4.1 Centralized AI training and the challenge of democratization

This massive cluster, running in public cloud data centers, was managed as a single unit (with a custom networking stack, gang scheduling, etc.) to enable researchers to seamlessly ramp up experiments without changing code [27]. Such centralized Kubernetes clusters or HPC setups are typical for cutting-edge AI labs—they concentrate computing in one location (or a few) to minimize latency between nodes and leverage specialized hardware at scale. Google’s DeepMind, for instance, uses Google’s TPU pods in centralized cloud regions for model training. While efficient in performance, this centralization means a relatively small number of data centers handle the majority of AI compute. As AI becomes critical infrastructure, questions arise about democratization: Can only big tech companies with multi-million-dollar clusters participate, or can computational power be more widely accessible? Centralization also creates single points of failure and can lead to resource under-utilization outside of peak research hours.

4.2 From volunteer computing to distributed networks

The idea of distributed volunteer computing has been around for decades as a way to democratize compute-intensive projects. A landmark example is SETI@home, launched in 1999, which enabled anyone with a PC to contribute to analyzing radio telescope data in search of extraterrestrial signals [28]. SETI@home packaged work units into a screensaver that millions of users ran on their home computers, collectively performing petaflops of computation. It proved the viability of harnessing idle computing power globally for a scientific task [28]. Other projects in the early 2000s (Folding@home for protein folding, BOINC for various academic problems) followed suit. These systems lacked monetary incentives for people who participated out of altruism or interest, but they demonstrated an important principle: Distributed compute networks can rival supercomputers if enough nodes join. The rise of blockchain technology introduced a new dimension to volunteer/distributed computing by adding economic incentives. Cryptocurrency networks inherently involve distributed and secure computations (albeit of a specific kind, such as hashing for Bitcoin), which inspired the concept of general-purpose decentralized compute marketplaces, where contributors (miners or node operators) get paid for completing arbitrary computing tasks.

4.3 Emergence of blockchain-based decentralized compute platforms

In recent years, several blockchain-based platforms for decentralized computation have emerged. Golem Network (on Ethereum) was one of the first, aiming to create a “global supercomputer” by letting users rent out CPU/GPU cycles in exchange for GNT/GLM tokens. It initially focused on use cases such as rendering CGI for graphics, but later expanded to include scientific computing and machine learning tasks. iExec (also Ethereum-based) similarly allows decentralized cloud computing with a marketplace for off-chain computation, secured by the iExec RLC token [6]. Both Golem and iExec rely on Dockerized tasks and sandboxing to run untrusted code on volunteer machines, with blockchain smart contracts handling payment and reputation. Beyond these, Akash Network utilizes a Cosmos-based chain to create a decentralized cloud, where providers auction off compute capacity for AKT tokens. Render Network (RNDR) connects individuals with idle GPUs to users requiring rendering or AI computing, utilizing RNDR tokens for payment [8]. DeepBrain Chain (DBC) has

built a dedicated blockchain to pool AI computing resources, enabling AI companies to train models on distributed GPUs at a lower cost, with DBC tokens serving as the exchange medium [7]. Fetch.ai, SingularityNET, Bittensor, and others have also explored combining AI services with crypto tokens. A common thread is that these platforms leverage blockchain to provide trust, facilitate payments, and promote openness in a distributed computing network: Anyone can contribute hardware, and users can trust the system to reward correct computation (using various verification mechanisms or redundancy checks).

Despite their innovative designs, current decentralized AI networks have yet to incorporate mechanisms for verifying renewable energy usage. The focus has been on technical and economic decentralization (who provides compute and how they are paid), rather than on energy transparency. In practice, a node operator on one of these networks could be using grid power of an unknown mix, or even running a diesel generator—the system does not account for it. Sustainability is not a key consideration in today’s transaction criteria. Integrating Granular Certificates (GCs and DeGCerts) into such platforms would enable the network to ensure that tasks are executed on machines powered by verified green energy. One could imagine, for example, a future version of Golem where each provider’s software is linked to a smart meter or certificate source: Before a task is accepted, the provider must present a DeGCert proving that the next hour of compute will be matched by (say) 1 MWh of wind energy from a nearby farm. Providers running on fossil energy would be outcompeted (or would need to buy DeGCert offsets). At the same time, those directly connected to renewables or who have procured granular certificates would earn the “green compute” badge. The combination of decentralized computing with granular energy tracking would ensure AI workloads are not only distributed and efficient, but also clean and accountable. The following sections delve into how, technically, we can integrate these certificates into blockchain-based AI networks.

5. Integrating granular certificates into blockchain-based AI

Today, granular energy certificates are typically managed *via* centralized registries or APIs provided by certificate-issuing bodies. For instance, an EnergyTag pilot might have a central database where 15-minute certificates are recorded and later queried by consumers’ software to certify their usage. To integrate such certificates with a blockchain-based AI platform, the first step is to bring certificate data on-chain in a traceable and trustworthy manner. By doing so, we replace centralized API calls (which could be prone to manipulation or error) with auditable on-chain records. Once certificate tokens or claims exist on the blockchain, smart contracts can automatically match and enforce energy-use policies for AI workloads. The key benefit is end-to-end traceability: Every kilowatt-hour associated with an AI task can be traced to a specific renewable source and time, with the record immutable on the ledger [9]. This drastically increases confidence and transparency. For example, a decentralized AI compute request could specify “requires renewable certificate proof.” The platform would then only schedule the job on nodes that can provably supply a recent DeGCert. Unlike a traditional system where one might trust a third-party auditor or a monthly report, the blockchain approach allows any verifier to independently check that for each task transaction, a corresponding certificate transaction exists (and has not been

double-counted). By marrying GC management with blockchain AI, we also gain the trustless and automated execution that blockchains provide—no manual reconciliation, but rather smart contracts ensuring that tokens (compute tokens and energy tokens) are exchanged appropriately when conditions are met.

5.1 On-chain tokenization

Migrating granular certificates onto blockchains raises questions of interoperability: Often, the certificate might originate on a different system or chain than the AI computing platform. There are a few patterns to consider. One is to have a unified blockchain that both the AI marketplace and the energy certificates use (e.g., if both the compute and energy markets operated on Ethereum, one could simply have an ERC-20 or ERC-721 token represent the certificates). This is not always feasible, as energy certificate systems might prefer specialized chains or need integration with physical grid data on a permissioned ledger. Thus, cross-chain solutions become relevant, where the AI platform's blockchain needs a way to trust certificates issued on another blockchain or database. Another approach is to tokenize the certificates onto the same chain *via* a bridge or oracle (discussed shortly). In any case, ensuring global interoperability of DeGCerts is crucial. One of the advantages of a decentralized approach is that it can remove regional restrictions: An AI node in Asia could obtain a certificate from a solar farm in Europe if allowed, broadening the supply of renewables beyond local siloed markets [22]. Smart contracts could also enable automatic trading and matching; for instance, if an AI job is about to run on wind power, a contract could automatically retire the corresponding certificate and attach it to the job's record, all in one transaction. To enable such features across different chains or systems (e.g., AI chain vs. energy chain), robust interoperability mechanisms are necessary.

5.2 Light clients/IBC for trustless cross-chain certificate verification

One trust-minimized way to integrate two blockchains (or a blockchain and a legacy registry) is *via* light clients and inter-blockchain communication (IBC). A light client is a simplified node that can verify block headers of another blockchain using just cryptographic proofs, without needing to trust a third party. Frameworks like Cosmos's IBC allow heterogeneous chains to exchange messages securely by each chain running a light client of the other [13]. For our context, imagine the AI platform runs on Chain A, and energy certificates are recorded on Chain B (which could be a consortium chain run by energy utilities, for example). Using light clients, Chain A can be made aware of the state of Chain B (specifically, of certificate token ownership or issuance on Chain B) in a trustless manner. If an AI provider claims "I have a 100kWh solar certificate for 9–10 AM," the proof would consist of a Chain B cryptographic proof (Merkle proof) that a certificate token is in the provider's address. Chain A's light client would verify Chain B's block header containing that token state. This is essentially how IBC works: Chains communicate data with verified proofs, so they "trust the chains, not a bridge" [13]. By implementing such cross-chain clients, we can achieve fully decentralized verification of certificates. Notably, Cosmos IBC has demonstrated billions of data exchanges between chains without exploits by relying on this model [13]. One hurdle is that light clients can be resource-intensive (especially if one chain is significantly heavier than the other). Still, developments in optimized light client protocols and succinct proofs (discussed shortly in ZKP)

are alleviating this issue. In summary, a light client/IBC integration would mean the AI blockchain natively understands and trusts the granular certificate blockchain's outputs, making the pairing seamless and automated.

Another approach is to use oracles, external services that feed data from the certificate system into the AI blockchain. For example, an oracle network like Chainlink or API3 could be tasked with querying a traditional certificate registry's API (or a private blockchain) and injecting a signed message into the AI smart contract, asserting that "X kWh of renewable energy at time Y" is valid for a given node. Oracles have the benefit of simplicity: They can interface with any off-chain system or different blockchain without the need for complex on-chain client proofs. Chainlink nodes, for instance, could be set up to monitor the EnergyTag registry. Whenever a certificate is issued or transferred, they relay that information (after reaching consensus among themselves) to the AI contract. The downside of oracles is the introduction of trust and potential centralization [29].

Suppose a single oracle or even a small federation of oracles is providing the data. In that case, users must trust that the data is honest and not compromised; the blockchain itself cannot verify the data's truth, as it only knows the oracle's report. This is known as the "oracle problem" in blockchain: The system is only as trustless as its data feeds [29]. For energy certificates, a malicious oracle could falsely claim a fossil-powered node had a renewable certificate. Decentralized oracle networks aim to mitigate this by utilizing multiple independent oracles and employing economic incentives to ensure correctness. Still, compared to light client approaches, oracle-based verification is semi-trustless. It might be acceptable as a stopgap or in scenarios where the certificate issuers themselves run the oracles (so essentially it is as trustworthy as the issuer). Oracles are certainly easier to implement with current tech; thus, many early integrations might use them. For instance, an API3 data feed could provide a "renewable percentage of grid for location Z at time T" to the AI chain, which the smart contract can use to decide if a node qualifies for green jobs. This would be a straightforward way to start, with the understanding that it relies on the oracle's integrity [29].

5.3 Bridge protocols for cross-chain with added trust assumptions

Beyond oracles, there are emerging bridge protocols that facilitate cross-chain data transfer with varying trust models. Protocols like Axelar, LayerZero, and Wormhole have gained prominence for linking blockchains. Axelar operates a decentralized network of validators who pass messages between chains (essentially a cross-chain router secured by a PoS consensus). For example, Axelar could carry a message from an energy blockchain to an AI blockchain, indicating that a certificate NFT had been transferred. The security relies on Axelar's validator set not colluding (similar to a mid-sized blockchain). Wormhole utilizes a set of "guardian" nodes (originally 19 guardians) to verify cross-chain messages; its trust is based on the majority of these guardians being honest. LayerZero takes a unique approach by using an independent Oracle and Relayer per message. A relayer delivers a message's proof, and the authenticity of its block header is attested by an Oracle (often Chainlink), so one must trust that neither is colluding. These bridge frameworks can certainly carry granular certificate data across chains. For instance, a certificate token on Chain B could be "bridged" to Chain A *via* Wormhole as a wrapped token, which the AI contract can then use.

The advantage of many bridge solutions is broad compatibility (they support many chain types) and flexibility. The disadvantage is additional trust assumptions or complexity; many high-profile bridge hacks (e.g., Wormhole's \$325 M exploit) show the risk when securing cross-chain assets. In context, if a DeGCert is bridged, one must ensure it cannot be double-used due to a bridge failure. Some recent efforts combine bridges with safety measures, such as rate limiting, monitoring, and insurance funds, to mitigate risks. In short, bridge-based interoperability can enable the flow of certificate information between different blockchain ecosystems, which is particularly useful when, for instance, the AI platform is on Ethereum. Still, energy certificates are on a bespoke energy chain. It is a practical approach, but it must be carefully engineered to avoid undermining the trustworthiness that DeGCert is supposed to convey.

5.4 Zero-knowledge proofs (ZKPs)

An exciting frontier is the use of Zero-knowledge Proofs (ZKPs) to verify cross-chain or off-chain information in a privacy-preserving way. Zero-knowledge proofs could enable an AI blockchain to verify that “a valid renewable certificate exists for X kWh at time T for node Y” without revealing all details or trusting any intermediary. For example, one could construct a zk-SNARK that proves a user owns an NFT on Chain B (the certificate) and that NFT corresponds to renewable energy in the needed time slot, then present that proof to a smart contract on Chain A. Projects like Succinct's zkBridge and frameworks like Polygon zkEVM's L2 ↔ L1 proofs are pioneering this approach. Essentially, a ZK circuit can embed a light client verification logic and compress it into a succinct proof that can be verified on another chain. Research prototypes (e.g., Harmonia by Belchior et al.) have shown that SNARK-based interoperability can achieve trust-minimized verification of another chain's state. In our scenario, a ZKP could prove that “in Chain B's state as of block 12345, address X had a certificate token of type solar, 15:00–15:15, 2025-07-21, 10kWh” and that proof could be verified by the AI chain's contract quickly, without needing to store entire headers. This method nearly eliminates the need for additional trust—it is purely math-based verification. Moreover, ZKPs can provide privacy advantages: the AI platform may not need to know the exact power plant or its price, only that it was renewable. A ZK proof can confirm the attribute (renewable) without exposing sensitive information (e.g., the producer's identity). This could alleviate privacy concerns for energy producers or consumers who may not want all details to be public. While current ZK tech has non-trivial overhead in setup and proving time, it is improving rapidly. In the coming years, we may see “zk- DeGCert” systems, where each certificate is associated with a proof that can be posted to any chain to validate the certificate's claims. The combination of ZKPs with DeGCert would yield a powerful result: a completely trustless, privacy-preserving verification that AI workloads are green. For instance, a data center could prove its consumption matched renewables every 15 minutes of last month, without revealing the exact load curve, using ZK proofs on certificate data. Such innovations would enable a verifiable green AI economy on-chain, with minimal leakage of competitive or personal data.

In summary, there are multiple pathways to integrate granular energy certificates with blockchain-based AI platforms. Each has trade-offs in terms of complexity, trust, and maturity of technology. A likely approach is a layered one, for immediate implementation, oracles and bridges can bring certificate data into AI marketplaces.

At the same time, the ecosystem can develop more trust-minimized solutions, such as IBC and ZK proofs, in parallel for the long term. The end goal is a DeGCert-powered, verifiable green AI economy: AI compute transactions automatically pair with renewable energy certificates, and anyone (from auditors to customers) can validate through on-chain evidence that an AI service was powered hour by hour by carbon-free energy.

6. Comparative analysis of GC and DeGCert

6.1 Comparing conventional GC and DeGCert models

Figure 1 shows that both Granular Certificates (GC) and Decentralized Granular Certificates (DeGCert) can be used interchangeably. Hence, this chapter conducts a qualitative analysis of both to demonstrate the effectiveness of the proposed DeGCert in comparison with the conventional GC in achieving transparent and sustainable AI.

In the conventional setup, renewable energy certificates are typically managed through centralized registries, which only ensure matching over long periods, such as monthly or annually. Although GCs are issued on an hourly basis, the reporting of these certificates usually occurs monthly. In contrast, DeGCert leverages on-chain management of fine-grained certificates.

From a transparency perspective, the GC model relies on reports from utilities or third-party auditors, which keeps the data siloed and not available in real time. DeGCert, being implemented on a public or consortium blockchain, provides an open ledger of all certificate transactions that any participant can query instantly [9]. This enables an AI consumer to verify that the exact amount of renewable energy used for a task was duly produced and certified, rather than waiting for a monthly sustainability report.

The trust model also differs significantly. Traditional GOs/RECs require trust in the issuing authority and assume that once a certificate is issued and retired, no double-counting occurs; however, the process remains opaque to the end user. DeGCert removes this dependency by encoding the issuance and retirement of certificates into smart contracts. This mechanism ensures that double-spending is impossible because the ledger rejects duplicate transactions. Any participant can verify the origin and authenticity through digital signatures and ledger proofs [9].

6.2 Overcoming regional barriers through decentralization

The decentralized nature of DeGCert also breaks down regional barriers that exist in the traditional system. Conventional certificate systems are region-bound, which limits efficient global matching. A DeGCert system on a widely accessible blockchain enables global interoperability, effectively turning the globe into a larger data center where anyone can contribute to AI computation. The only eligibility requirement is verifiable proof that the energy originated from renewable sources, which DeGCert provides globally.

Smart contracts can enforce rules to respect local regulations, such as executing computation only when the grid has surplus renewable energy. This establishes a foundation for a demand-response system that can utilize available green energy within the grid. It can also enable, for instance, a European AI workload

to be matched with overnight wind power from another continent, if both parties agree—something that is very cumbersome under today's certificate regimes. Such flexibility can reduce costs and enhance the global utilization of renewable energy.

6.3 Real-time matching and automation

The automated and programmable nature of DeGCert, facilitated by smart contracts, allows real-time matching and settlement. In the GC system, an entity reconciles its certificates on a monthly or yearly basis. With DeGCert, as an AI job executes, a smart contract automatically allocates and retires the necessary granular certificates on a minute-by-minute basis. This automation reduces administrative overhead and ensures precise accounting with no delay.

It effectively enables the concept of 24/7 renewable matching as advocated by initiatives such as Google's carbon-free energy program through code enforcement. The result is that AI cluster operations can be continuously monitored by software that checks if sufficient DeGCerts exist; if not, it can throttle non-critical workloads to maintain a 100% clean profile.

6.4 Scalability comparison between GC and DeGCert

A potential concern lies in scalability to handle millions of certificate transactions on-chain. However, energy attribute transactions are relatively low in volume compared to financial transactions, and solutions have already been proposed to aggregate the thousands of energy certificates using the Distributed Ledger Technology (DLT) of IOTA, which utilizes the no-fee transaction model of IOTA [26]. Modern blockchains and layer-2 networks support high throughput, while techniques such as batching or zk-rollups can further increase capacity. These developments indicate that a global DeGCert system is technically feasible.

6.5 DeGCert as a stronger foundation for sustainable AI

Since DeGCert is more effective than GCs in supporting sustainable AI, it is far superior to conventional volumetric energy certificates. Under the REC/GO system, an AI company might claim that it purchased enough wind RECs to cover last year's usage. Stakeholders must trust the claim based on external audits, but it does not guarantee that the AI was run on renewable energy at every moment.

With DeGCert, a company can instead prove that every interval of its AI computation was matched with renewable certificates on-chain, with verifiable public ledger proofs. This statement is far stronger and backed by direct evidence. It also encourages companies and data centers to consume clean power during each operational interval rather than buying offsets after the fact [21].

DeGCert aligns incentives for actual 24/7 carbon-free operations. Smart contracts can even be configured to execute AI workloads only when matching certificates are available, directly linking AI activity with renewable generation. This approach reduces reliance on fossil-based peaker plants and ensures that sustainable AI becomes a verifiable operational reality rather than a paper-based claim.

Table 1 offers an in-depth comparison highlighting how the proposed DeGCert improves upon the conventional GC approach.

Aspect	Granular certificates (GC)	DeGCert
Management Model	Managed through centralized registries	Managed through decentralized blockchain (public or consortium)
Certificate Issuance & Reporting	Certificates may be issued hourly but reported monthly or annually	Certificates are issued, matched, and retired on-chain in real time
Transparency	Relies on reports from utilities or third-party auditors; data remains siloed and delayed	Provides open, real-time access to all transactions via public ledger (auditable by anyone)
Trust Model	Requires trust in a central authority; opaque to end users	Trustless system—smart contracts handle issuance and retirement; double-counting is impossible
Verification Mechanism	Based on periodic audits and manual verification	Automated, cryptographically verifiable through digital signatures and ledger proofs
Regional Scope	Region-bound; limited interoperability across markets	Global interoperability; certificates can be verified and exchanged worldwide
Regulatory Adaptability	Must comply with region-specific registries	Smart contracts can encode and enforce local regulations automatically
Demand-Response Integration	Limited or manual coordination	Enables automatic demand-response by executing workloads when renewable surplus exists
Real-Time Matching	Monthly or yearly reconciliation	Minute-by-minute automated matching and settlement via smart contracts
Automation Level	Manual processes and administrative overhead	Fully automated through programmable smart contracts
24/7 Renewable Matching	Post-factum matching (offset-based)	Enables continuous 24/7 renewable tracking and enforcement
Scalability	Scalable due to simple database-driven APIs	Scalable through Merkle Tree-based aggregation
Operational Efficiency	Periodic reporting creates lag and inefficiency	Real-time automation reduces delay and overhead
Proof of Renewable Use	Based on ex-post claims (e.g., annual REC purchases)	On-chain proof that every operational interval used renewable energy
Suitability for Sustainable AI	Indirect assurance of sustainability; relies on offset logic	Direct assurance—verifiable, automated, and enforceable renewable matching for AI operations
Example Use Case	AI firm claims annual renewable coverage based on past REC purchases	AI cluster proves every computation interval used clean energy with on-chain verification

Table 1.
Comparison between conventional granular certificates (GC) and decentralized granular certificates (DeGCert).

7. Future work

Looking ahead, several research and development directions can extend the DeGCert framework to strengthen its impact on sustainable AI. The section outlines the most promising pathways.

7.1 Carbon-aware cluster orchestration

A crucial step toward sustainable AI is the development of carbon-aware orchestration for compute clusters, as existing auto-scalers in Kubernetes (K8s)

and Slurm respond to resource utilization or cost but overlook carbon intensity and renewable availability. Next-generation schedulers can integrate live carbon data or DeGCert availability to scale workloads when renewable energy is abundant, utilizing custom Kubernetes controllers, Carbon-Aware APIs, and node selectors to launch jobs during solar or wind surges while pausing or queuing them during periods with higher fossil fuel usage. By linking DeGCert issuance to scheduling, each job can be authorized through a renewable certificate. Research prototypes, such as the Carbon-Aware Kubernetes Scheduler (CAKS) and other energy-aware orchestration frameworks, have demonstrated emission reductions of 15–25% with minimal performance impact, supporting the vision of 24/7 carbon-matched AI at scale. In decentralized AI networks like Akash, DeepBrain Chain, and Render Network, nodes operating private K8s clusters can adopt certificate-aware scaling to deliver verifiable clean-energy compute, acting as micro data centers that expand or contract with renewable supply, thus forming an energy-elastic decentralized AI ecosystem. While prior work has focused on centralized systems, this study advances carbon-intelligent orchestration to trustless, blockchain-based AI environments, enabling certificate-based accountability and sustainable scalability across decentralized compute markets.

7.2 Blockchain for renewable verification and incentivization

A complementary direction is embedding sustainability logic directly into blockchain protocols. A conceptual “GreenAI Network” could reward nodes powered by verified renewables, combining decentralized compute markets with proof-of-green mechanisms using IoT sensors or utility APIs. Nodes presenting valid DeGCert proofs would receive higher rewards or task priority—for example, solar-powered nodes could earn 1.5× more tokens. Smart contracts would enforce continuous audits of energy provenance, creating a verifiably clean decentralized AI cloud that fuses energy informatics, AI scheduling, and blockchain consensus.

7.3 DeGCert ledger and fractional energy accounting

A dedicated DeGCert ledger—or DeGCert Chain—could automate certificate issuance, trading, and retirement *via* smart contracts. Renewable plants would mint certificates in the form of Verifiable Credentials (VC) of Self-sovereign Identity (SSI) for 15-minute generation blocks, allowing AI workloads to claim fractional certificates for small energy units. Integration with stablecoins or CBDCs would enable automatic settlement, while decentralized oracles cross-verify grid data to prevent fraud. This open ledger would connect real-time renewable generation with AI consumption, fostering transparency and traceability. It could also enable financial innovation—AI firms pre-purchasing certificates to hedge energy costs, and renewable developers leveraging on-chain demand signals for financing—thereby strengthening the economic link between AI expansion and clean energy growth.

7.4 Hybrid interoperability and policy alignment

Future deployments will combine centralized clouds and decentralized AI networks, requiring interoperability standards for transferring certificate proofs between corporate and blockchain ecosystems. For instance, Google’s 24/7 carbon-free energy

data could be shared in DeGCert format for decentralized workloads, while independent compute providers could sell clean certificates to data centers. Organizations like the Energy Web Foundation can develop APIs and gateways to bridge these ecosystems.

Collaboration with policymakers and standards bodies will ensure alignment with frameworks such as the GHG Protocol Scope 2 [21], allowing blockchain-based certificates to be accepted as verified renewable evidence.

7.5 Technical and policy challenges

Scaling DeGCert requires overcoming technical and institutional challenges. Technically, it must handle billions of certificate events from IoT meters and AI workloads, achievable through Layer-2 solutions, off-chain proofs, and decentralized storage. Policy-wise, adoption must align with energy regulations, privacy laws, and carbon reporting protocols. Collaboration among regulators, cloud providers, and standards agencies will prevent fragmentation and promote the open adoption of standards.

7.6 Future outlook

Collectively, these directions form a roadmap for sustainable AI through DeGCert. Carbon-aware orchestration aligns compute with renewable supply, blockchain verification ensures transparent energy attribution, and a public DeGCert ledger enables fractional accounting and financial incentives. Interoperability will unify centralized and decentralized systems, while addressing scalability and governance will make DeGCert both technically robust and institutionally credible—laying the groundwork for a verifiable, 24/7 carbon-free AI future.

8. Conclusion

DeGCert establishes a verifiable foundation for 24/7 renewable-powered AI. By binding energy provenance directly to AI workloads through blockchain-based proofs, DeGCert transforms sustainability from pledges into provable actions. Unlike traditional REC or GO systems, which rely on aggregated annual accounting [21], and GC, which typically aggregates accounting every month, DeGCert provides real-time, auditable visibility into every 15-minute computation cycle. This temporal precision ensures that AI operations transparently reflect actual renewable usage rather than statistical averages.

DeGCert adoption also generates powerful market incentives. Linking AI demand with verified clean supply drives investment in renewable capacity and storage, accelerating the global energy transition. As renewable generation grows, the transparency DeGCert provides will help identify and address remaining gaps in clean coverage, promoting informed grid planning and innovation.

Realizing this vision will demand collaboration across disciplines. Blockchain technologists, AI engineers, utilities, and policymakers must collaborate to develop the standards and infrastructure for interoperable, scalable, and trustworthy energy certification. The future work outlined above, ranging from carbon-aware orchestration to hybrid interoperability, will guide that evolution. Together, these efforts can ensure that as AI becomes more central to our societies, its energy foundation remains transparent, accountable, and clean.

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Trustworthy AI in Smart Grid Systems

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Abstract

As smart grids increasingly rely on AI for energy distribution, demand forecasting, and fault detection, the trustworthiness of these systems becomes critical to their successful deployment and public acceptance. Ensuring responsible decision-making involves protecting sensitive consumer and operational data, building models using ethically sourced and representative data, and developing explainable models that promote transparency, accountability, and user engagement. This chapter addresses the foundations of ethical AI and the challenges it presents in today's smart grid systems, examines the challenges of identifying and mitigating bias in AI models used in critical infrastructure, explores the importance of fairness in these systems and strategies to ensure it, and provides an overview of predictive maintenance with trustful AI in smart grid environments.

Keywords: artificial intelligence, machine learning, ethical AI, fairness, explainable AI(XAI), trustful AI

1. Introduction

Smart grids represent the next evolution of electrical power systems, combining advanced information and communication technologies with the traditional grid to enable two-way flows of electricity and data. Artificial intelligence (AI) is a key enabler in smart grids, offering capabilities such as predictive analytics for demand and supply, autonomous grid control, and optimized integration of renewable energy sources [1, 2].

Smart grids powered by AI have emerged as potentially game-changing methods for enhancing the dependability and durability of electricity networks, significant benefits can potentially from grid efficiency, reliability, and sustainability [3]. With the assistance of smart infrastructure powered by AI, the distribution and effectiveness of energy could endure a significant transformation [4]. This includes but not limited to [5]:

1. New challenges in keeping track of any regulating individual node from centralized power circuits, because power infrastructures can utilize sophisticated algorithms even with real-time data.
2. Intelligent smart grids employ innovative sensing and monitoring technology. Decisions based on collected data regarding load balancing, voltage regulation, and defect detection may enhance the power grid's performance and efficiency [6].

3. Smart grids driven by AI employ prediction and decision-making systems based on machine learning, which must be governed and decentralized [7].

The use of AI approaches is becoming more popular as they offer strong and promising tools for controlling and analyzing stability in smart grids [8]. However, the deployment of AI-driven solutions in smart grids also raises complex questions such as listed in Ref. [9]: strict data requirements, unequal learning, AI interpretability, challenges with learning transfer, AI resilience for interacting quality, and AI resilience against adversarial examples or attacks. Therefore, it has raised the demand for trustful AI systems to ensure reliable AI models, deployments, and model explainability supporting decision making.

The remainder of the chapter is organized as follows. Section 2 details the ethical AI, outlining the foundation, principles and operation in trustworthy AI in smart grid system. Section 3 presents the importance of bias either from data source, algorithm, or AI deployment, The consequence of bias and how to mitigate them with liability concerns. Section 4 discusses the role of AI in asset monitoring and failure prediction and the need for explainable AI. Section 5 concludes the paper by summarizing findings, outlining future research directions, and highlighting the broader significance of trustful AI adoption in smart grids.

2. Ethical AI

2.1 Ethical foundations of trustworthy AI, data privacy, and security challenges

AI has been around for a long time, but only recently caught attention due to the increased easy access to generative artificial intelligences and large language models like ChatGPT. AI has also been used in the industry for a long time for specialized purposes, regarding pattern recognition in images, gaming, signal processing and similar. Common for all is that AI requires data for training sessions, and while AI promises a lot, outputs are still a result of the quality of the training, which is an ongoing research activity. In that aspect, a key characteristic for a useful AI is that output can be trusted. An AI that cannot be trusted is not very useful, no matter the application of the AI. Due to the potential of AI, the problem of being trustful or not is so large it is the focus of the main industrial drivers as well as state-level organizations. The European Union, for example, provides dedicated guidelines for what trustworthy AI in its entire lifecycle is all about [10]:

- Lawful AI that respects countries individual laws and regulations
- Ethical in the sense that the AI adheres to ethical principles and values
- Robustness, both technically and socially

These three elements have already shown to be challenging.

Lawful AI: Obtaining useful training data for the AI—while useful to collect whatever, an ethical AI must adhere to legislations of a particular country. This is not trivial since not all countries share the same laws and interpretations of laws, and since AI code easily migrates across nations boundaries, it is extremely easy for a successful AI to violate a country's legislations, see Ref. [11].

Ethical AI: Ethics shares similar problem, since ethics may also differ at a demographics level. For example, output from ChatGPT have shown undesired bias toward genders [12], or Tesla's Grok showed at some point antisemitic behavior [13]. In both cases, the AI can cause harm by not obeying ethical rules. *Robust AI:* Technically an AI is required to be robust, not only at an operational level, but also provide results that are in line with the truth. The latter means that AI's should not provide false, or commonly known, hallucinated results, which may have dire consequences, see, for example [14]. This can happen for example if the input training data is of poor quality, or poorly selected, leading the training to become not very useful.

2.1.1 Stakeholders in AI and ethics of AI

There are different stakeholders when it comes to AI and thereby also implications of the ethics used AI. The stakeholders have very different interests which poses a challenge to define a common set of ethics using AI in general. *Academia:* Researchers and research communities which requires freedom to explore new usage and mechanisms for AI. Any limitations will potentially challenge the freedom of doing research. Collection of data for training is typically challenged by privacy concerns of those that owns or is described by the training data. However, AI may also be used to speed up research activities. *Governments:* Each government have some objectives, wherein data may be useful to locate and mitigate inefficiencies, locate potential threats against its society, or protect resources against trickery and cheating. For many places, for example, Denmark, the vision is that AI will enable huge cost reduction in the public sector. In most democratic and free societies, intentions are usually good in the sense that use of AI is argued by benefit of the society, while in more restricted societies, reasons of using AI may be more sinister. Either way, intrusion of citizen privacy is a great concern in many use cases.

Intergovernmental entities: United Nations or the World Bank are responsible for raising awareness and drafting agreements for AI ethics globally. These entities seek to use AI for the common good of humanity in dedicated use cases, for example, education or justice.

Non-profit organizations: Groups like Black in AI or Queer in AI are dedicated to shift power dynamics of AI ecosystems to ensure specific voices are heard in development, deployment, and regulation of AI technology usage. For example, specific bias toward black people caused by biased input material for training should be avoided.

Private companies: Any company that exploits data may rely on and use AI. Most well-known are larger companies like Google, Meta, and Microsoft with generative AI, but also banking, consulting, health care, and weapon industry, for example, drones, have started using AI in a larger scale to either reduce cost of operation but also for increased service levels. Those companies that have a direct link to citizens will be challenged by privacy issue in relation to input data for training the AI.

Technology providers: At the end of the day, AI must be executed somewhere, and companies like Nvidia provide technology targeted to support efficient AI execution. This creates a push for more-sales and revenues for supporting more AI being used, while also requiring more resources to manufacture and operate the hardware.

Energy systems: The large success of AI today creates the need for a large amount of electronic equipment constantly processing data. This is energy demanding, and AI cannot any longer be considered at a scale, without considering it requires energy that leaves a significant CO₂ footprint. In addition to this, these also benefits from AI as it can be used to optimize complex control of energy and power flows.

The interests of the stakeholders are not aligned very well and indicate both good and bad consequences for individuals and the society, meaning that setting up guidelines and ethics is not a trivial task. With the industry as the driving forces, the use of data that may easily violate privacy of users is a key challenge, as it has been seen before with Facebook, Google, etc., who's business models have been centered around collecting data from end users. Legislative orders have in some cases been introduced to guarantee other feasible ways, for example, payment models.

2.1.2 Privacy and security challenges

The need for training data, and particularly the quality of input data, to guarantee that AI meets the requirements of ethical standards, leads to a number of challenges related to privacy of end-users if the functionality requires such type of input. The overall process of collecting, storing, and processing data requires several steps that (1) are hidden from the end-users, hence requiring trust from the end-users that data is being handled in an expected way, that is, there are generally no way to validate that a promised process is also the actual process and (2) that data is not also being exchanged as commodities among third parties. Again, it is hard to validate if a company sells private data from end-customers. Even in the case, where a company complies with regulations and offers a transparent data handling process, there is no clear guarantee that the same company has not been exposed to cyber-attacks with a purpose of stealing data from the said company, thereby leaking potential sensitive data.

A particular problem exists with using data from consumers in low-voltage grids, since these may potentially directly link to a person hereby challenging existing GDPR regulations. This causes the distribution system operators to handle such data with extreme care and is often a barrier for carrying out research for developing and testing new smart algorithm for smart grids in particular. The situation is no different when AI is employed in the training, because it too will require user-specific data for training. Therefore, research in this area is often delayed due to lawyers requiring agreements to be setup with guarantees of securing data during research. This puts further cyber-security requirements to the host universities that supplies the IT infrastructure to store data. Requirements such as *retrieving, storing, deleting, sharing, processing*, and more raises a long list of legal questions that can be really hard for researchers to handle in a simple and quick way. Further, plans and strategies on handling if leaks happens must also be in place. For research in particular this is often done in collaboration among different partners further complicating any agreement that allows sharing and use of data. For companies, this process can be even harsher as they have a financial incitement of using user data with an artificial intelligence system. A few simple human mistakes even made in good faith, may lead to leakage of data under GDPR protection, which for any company or institution may have severe consequences and not least for the customers.

2.2 Principles of ethical AI

In Ref. [15], a set of clusters were found describing ethical principles: transparency, justice and fairness, non-maleficence, responsibility, privacy, beneficence, freedom and autonomy, trust, sustainability, dignity, and solidarity.

Fundamental rights: Ensuring the human rights for those citizens exposed to the decision of AI is critical, independent of the application. For that, transparency is

a critical aspect that needs to be respected, which needs to be considered from even the early design decisions when implementing and deploying the AI. For example, consider the use of Bayesian networks (see eXplainable AI, XAI [16]) as opposed to neural networks that works as a black box, have implications on the transparency of the decisions or conclusions made by the AI. This, in turn, affects trust in using the AI and ultimately how useful the AI may be. On the other hand, the choice between those two types of AI technology may very well be influenced by a range of technical requirements and possibilities for deployment and execution. With transparency, accountability is also achieved, since a transparent decision process of an AI also enables backtracking to what was critical for a particular decision to be made in immigration cases as opposed to enabling more automatized processes where no or little human assistance is strictly required, see for example [17] which implies human-in-the-loop work processes in combination with AI algorithms rather than just relying on AI.

Ethical principles: Another aspect influencing these aspects is related to the selection of training data, which if not done properly, leads to issues like bias, overfitting, underfitting, and in addition to that, if data initially needs to be cleaned, for example, to match a specific input format. A lot of added and hidden work, where each steps can be done wrong and lead to poor training, may thereby affect the quality of the AI and thereby the performance, for example, precision and accuracy of the AI output. In turns, this may have a negative impact on some of the fundamental rights of humans, for example, a wrong decision based on AI whether a person can get a visa granted or not for traveling to a country may not be caused by the AI itself, but the selected training data that finally disallows the person to the specific country.

Requirements to AI: Finally, the amount of AI that requires training today also requires vast amount of computing power and thereby electric energy. While it not directly implicates any of the usual ethical principles, it is critical for the human survival that we do not burn more fossil fuels, and in the case of training AI an aspect of what is meaningful and what is not meaningful becomes critical. Some applications of AI seem more useful than others, for example, for smart energy systems [17] as opposed to waking dead people with AI [18].

2.3 Ethics in smart grid operation

Smart grids are defined by electrical grids with a responsive and intelligent behavior toward loads and demands that allows a high degree of uncertainty from renewable energy production to exist in modern electric infrastructure. AI is more and more often seen as a part of the solution to many of the challenges, based on the complexity of analyzing data measured in a distributed context of varying quality and considering different time horizons. In particular at distribution level of the electric infrastructure, AI is used for analyzing measurement data and perform predictions, estimating model parameters, detection of faults, and anomalies [19, 20]. In particular, the introduction of digital twins in collaboration with AI allows support for complex application for even small-sized DSO who cannot afford large-scale systems from well-known vendors.

Two critical aspects of using AI in smart grids are: (1) privacy considering that many measurements are household data, which may reveal a lot of individuals personal lifestyle and behavior, and (2) accountability if some application fails with severe consequences caused by AI-based decision. Who is to blame, if the decision is based on a black-box type of AI. In this case, it may not be easy to account for

decisions. Any safety limits must be respected, since an electric grid is a part of our society's critical infrastructure. This has implications for how to obtain training data and train AI's for grid operations. Creating training data for fault identification, for example, requires a large amount of data that has been measured when faults occur. Even if faults happen frequent enough to ensure enough training data, it is not always that measurements are available, for example, due to the faults impact on measurement devices. Worse, faults do not happen so often, so lack of data is very real problem for training AI's. To mitigate this problem, laboratories such as [21], or digital twins [22], allow to introduce faults and measure impact that can be used for training, but at the cost that the training data is built on models and simulations of the real world, and not real world itself. This in turns puts requirements to the models and equipment used to generate data. Models are only as effective as the model is capturing the essence of what is being modeled, and faulty situations are often very complex and caused by situations not foreseen, hence not easily modeled. Therefore, this calls for additional research in classical modeling and evaluation methods to support the usage of AI in the industry and to harvest the benefits of AI in smart grid systems.

2.4 Human-AI collaboration in energy management

Energy management is critical from both an operational point of view as well as a market point of view, since trade is done in terms of energy bulks of various sizes and durations. As a part of energy being critical for the society, humans must be in the loop of operations for the overall safety. The interaction between human and system is in this context critical as it is easy to overwhelm humans with information which may be counterproductive. AI may play a key role to ensure that the complexity of operating the grid can be reduced to a digestible flow of meaningful information for human operators. The usage of AI in this context should be viewed with considerations of experts who worked and gained a lot of experience with systems and how they behave. Such expert knowledge may be strictly required encoded as well, as to guarantee that valuable know-how is not lost if the key expert must leave the position, for example, retirement. The criticality of the interaction between human and AI-based energy system management is the trust in the support given by AI. Consequences of wrong decisions may be severe, and for the system and AI, these may not be critical since in worst case, the system will simply not be used after failure. But for the human operators, wrong decisions, even if triggered by AI supported systems, will possibly psychologically haunt the person or persons that enabled the consequences of a poor energy management. On the other hand, AI-based systems may also assist operators in making poor or dangerous decisions. Lessons from, for example, the Chernobyl accidents illustrates the severe impact of poor energy management, based on a bypass of computer aided support due to human errors [23].

Safety in operating energy system have always been critical to these kinds of systems, due to the large amount of energies involved in the system, and the impact this has on the society. Both humans and AI can fail or make poor decisions, but the combination of poor decisions from both sides, can be expected to lead to large-scale impact. History shows that in such cases; society needs to find and punish the responsible. This may be hard if black-box AI has been used to make decisions that combined with poor human judgment, leading to a large accident. Who is to be blamed? Maybe the operator just followed the recommendations of an AI—is it then the operator's fault or the AI's? If it is the AI, then did someone train the AI poorly? Such questions bring the use of AI in energy system into laws and regulatory institutions.

The issue of training AI's is not only valid for the AI-based system, but also operators require training to be able to properly understand and assess the output of the AI to reduce risk of the type of dual failure, where both human and AI fail. If this can be done successfully, then this will instead reduce the risk of using AI, since both AI and human may hinder each other to create catastrophic scenarios. So, with the training, also education of operators must be considered. The conclusion must be that bringing AI into the context of energy control and management requires a much broader view of AI, as it involves workflows, legal and regulations as well as technical solutions, which has to be designed, developed, and tested in conjunction with each other to guarantee that the correct requirements are captured before system deployment.

2.5 Privacy challenges in smart grid data collection

Historically, data about consumption has been collected either manually or by radio interfaces, to provide insights enough to bill the end customer. This is the result of a natural business case, that the customer pays for the electric energy they consume, but with the introduction of smart grid this change. Smart grid operations at distribution level, such as congestion management, [24], predictive maintenance, [25], loss calculation [26], requires the measurements from a metering infrastructure. Modern smart meters can measure a quite high number of parameters, for example, voltages, currents, power (active and reactive), system frequency, harmonics, and several events for three-phase systems, which creates a lot of data useful for the smart grid operations. The caveat is that the same type of information can be quite revealing about the customer connected to the smart meter and can be used in context not intended for. Examples could be thieves that wishes to detect if someone is home in a house, and by looking at power consumption patterns can establish a safe time to break into the house. Other examples could be the local authorities that pays social support based on a person living alone, can check if this person has a loved one living in the house as well, hereby not fulfilling requirements to receive social support, or in combination with other types of data can establish a picture of the person/persons living in the house; if light is switched on to the toilet many times every night, one may from the electric power pattern reveal that there is someone in the house having health issues. This information can be useful in other context, for example, black mailing purposes. So in general, the system operators who has access to the measurements for the purpose of efficiently running their grid and, thereby providing electricity to the end customers, also requires protecting their data. This poses challenges when AI needs to be trained to support smart grid operations, since not only practical legal agreements and security handling mechanisms must be established, but also procedures on how to handle leakages must be established. Anonymization of data may be done *via* first establishing the purpose of use, for example, prediction of consumption may not require grid topology; hence, stripping geographical data from measurements may be enough to not be able to trace back data to single persons. More complex it becomes if the topology data is required in combination with measurements, but also here, stripping the topology from geographical locations enables anonymization since it is extremely difficult to track back a topology to a specific geographical area. Further steps to convert a geographically correct topology into a fixed grid topology make it even further impossible to identify the grid, and thereby also any data to household owners. Aggregation of consumption into junction points is another way to ensure that it is impossible to perform the kind of analysis that may challenge GDPR rules and legislations.

3. Fairness and bias in smart grid AI systems

AI has the potential to revolutionize many industries and improve people's lives in countless ways, also including smart grid applications. However, one of the major challenges facing the development and deployment of AI systems is the presence of bias [27], addressing the need for fairness as a mitigating principle.

Fairness is defined as the absence of any prejudice or favoritism toward an individual or group based on their inherent or acquired characteristics [28, 29]. The absence of fairness can be caused by a bias, which is a systematic error or distortion from the actual state of affairs due to flaws in data collection and processing, study design, analysis, and interpretation [30]. In the context of AI, bias can arise from various sources, including data collection, algorithm design, and human interpretation. Machine learning models, which are a type of AI system, can learn and replicate patterns of bias present in the data used to train them, resulting in unfair or discriminatory outcomes.

The following sections give an overview of bias that come from data sources and decision making process, and also cover the mitigating techniques.

3.1 Sources of bias in energy data and algorithms

Bias can come from data, training models, and users involved. Firstly, smart grid algorithms are trained on vast datasets of energy consumption, grid performance, and user behavior. If such datasets are not representative of the entire population, or if they reflect existing societal inequalities, the algorithms trained on them will inevitably inherit and amplify these biases. Secondly, machine learning can also contain bias if the algorithms are based on biased assumptions or biased criteria are used during the decision making [31]. Last but not least, user can also introduce bias into the system when they use AI systems, either consciously or unconsciously [27].

Data bias occurs when the data used to train machine learning models are unrepresentative or incomplete, leading to biased outputs; more specifically, it can be caused by inadequate data and biased data [27].

- **Inadequate data:** Infrequent and specific patterns may be down-weighted by the model in the name of generalization and so minority records can be unfairly neglected. This lack of data may not just be because group membership is small; data collection methodology can exclude or disadvantage certain groups (e.g., if the data collection process is only in one language). Sometimes records are removed if they contain missing values and these may be more prevalent in some groups than others.
- **Biased data:** Even if the amount of data is sufficient to represent each group, training data may reflect existing prejudices (e.g., that female workers are paid less), and this is hard to remove. Such historical unfairness in data is known as negative legacy. Bias may also be introduced by more subtle means. For example, data from two locations may be collected slightly differently. If group membership varies with location, this can induce biases. Finally, the choice of attributes to input into the model may induce prejudice [32].

Such data bias can happen during the data collection: Bias can manifest in three primary stages—data collection, integration, and preprocessing. During the data

collection phase, bias may arise from raw data acquisition and the utilization of secondary data. Raw data may inherently contain biases due to measurement inaccuracies, sampling, or selection processes. Similarly, secondary data can introduce biases through sampling and selection procedures. Subsequently, data integration can introduce aggregation bias, while data preprocessing can potentially introduce measurement and aggregation biases. If left unaddressed, these biases can culminate in representation bias, impacting spatial and temporal scales within smart grid systems [32].

Algorithm bias occurs when the algorithms used in machine learning models essentially contains biases, which can happen when algorithms are based on biased assumptions or when they use biased criteria to make decisions [31]. For example, an algorithm designed solely to minimize the overall energy costs might prioritize serving large industrial consumers over residential areas, or favor areas with predictable demand patterns over those with variable or lower demand, potentially disadvantaging vulnerable communities.

Moreover, these biases can *propagate* throughout the ML algorithm development pipeline. The design of ML algorithms' loss and reward functions can also exacerbate overall bias. Careful consideration is needed to ensure these functions do not disproportionately penalize certain groups, promoting unfairness in algorithmic decision-making. Evaluation bias is another concern during model performance assessment, mainly when using metrics like accuracy or imbalanced datasets. During post-development, the ML models' deployment phase introduces its own biases. Domain shift bias occurs when the data distribution of the training model differs from its actual deployment environment [32].

Many ML models' inherent "black box" nature make their decision-making processes opaque. Encouraging interpretable and explainable models and documenting model decisions can help address this concern.

User bias can happen when users provide biased training data or when they interact with the system in ways that reflect their own biases [27]. Fairness is important in AI algorithms to suppress the effect of bias, and thus ensures that AI systems treat all individuals and groups equitably and without any form of discrimination [27].

Diagram from paper [32] (shown in **Figure 1**) illustrates a high-level mapping of critical bias points and their potential propagation paths, see details in the paper.

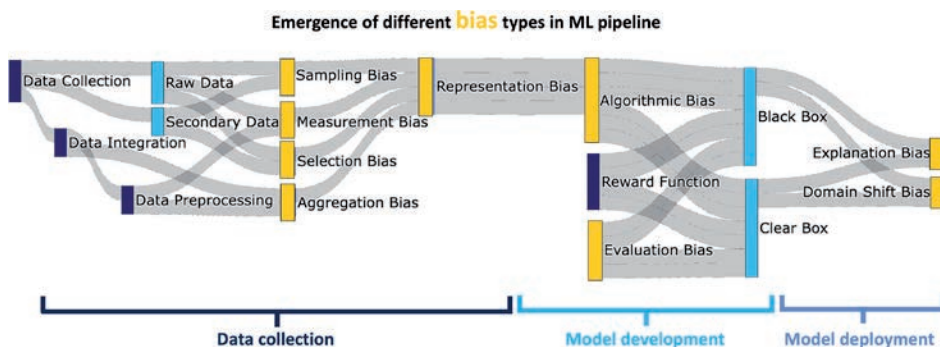


Figure 1. Connecting hurdles, their origins, and their impacts throughout the ML cycle [33].

3.2 Impact of unfair decisions on consumers and stakeholders (engagement of users and decision makings)

Unfair decisions, either coming from bias data or bias algorithms, can have negative impacts on the society, as it may potentially overlook or misrepresent the groups in the society.

Energy justice, a recently emerged focus for researchers and policymakers, aims to reduce the impacts of bias in the decision system and then to bolster energy equity [34–36]. It advocates for equal access to affordable and reliable energy supply and services for all, particularly emphasizing the needs of underserved communities with three main components—recognition, distributive, and procedural justice [33, 37].

Distributive justice revolves around the ethical principles that should guide resource allocation among society members. Finally, procedural justice emphasizes the integrity of the process leading to decisions.

3.3 Techniques for ensuring algorithmic fairness

Anticipating bias-free data is almost unrealistic, as pointed in Ref. [38], because diverse techniques have been used to collect socioeconomic, weather, physical, built environment, and energy data on varying social, spatial, and temporal scales from diverse sources in different formats. The imperative is to minimize bias to ensure fairness, equity, and accuracy in models. So, the first step to mitigate potential impacts on AI models from bias data actually is to recognize them and then later mitigate. Bias can be discovered in various ways, as noted in Refs. [32, 35], such as examining the training data for representativeness, analyzing algorithmic output for patterns of discrimination, and seeking feedback from affected stakeholders.

More recently, a thread of research has focused on changing data representation to improve fairness. Several techniques have been proposed predicated on either philosophy of fairness through unawareness or fairness through awareness. In the former, the logic is to learn a new representation for individuals independent of their protected attribute while preserving other information, and the latter focuses on achieving fairness while considering protected group information [39]. Zemel et al. [40] proposed mapping individuals to a new distribution that protects the protected group information while retaining other information. The authors [41] follow up this idea by using a variational auto-encoder to make the sensitive attributes independent of the latent representation and applying further learning to that representation.

Mitigation can be employed using different strategies. For example, data preprocessing along with data augmentation or bias removal can be applied in the early stage to ensure the training data is balanced and well represented of all relevant groups; algorithms can be modified to identify and correct bias data—including adjust the weights of certain features, incorporate fairness constraints into the optimization process and so on [42]. Furthermore, postprocessing corrections involve applying adjustments to the outputs of AI models can also be used to ensure fairer outcomes, such as re-ranking or recalibrating predictions to align with fairness criteria [43] can improve AI outputs. Recent works have been proposed either to remove or to alleviate data bias during training deep learning models, such as in paper Nam et al. [44] train an intentionally biased auxiliary model in the meanwhile enforcing the main model to go against the prejudice of the biased work. Xu et al. [45] have extended the model to be applied to distributed settings like federated learning to tackle biased models in

classification problems of images. To the best of our knowledge, there is no work yet on smart grid system, but can be a promising direction in near future.

4. Predictive maintenance with trustful AI

4.1 The role of AI in asset monitoring and failure prediction

In recent times, the traditional maintenance policies, including periodic inspections and run-to-failure, are increasingly becoming inadequate for today's stressed grids. Developments in machine learning (ML) and AI have shifted asset management toward condition- and risk-based data-driven decisions. This is achieved by fusing Supervisory Control and Data Acquisition (SCADA¹), Intelligent Electronic Devices (IED) logs, thermal/infra-red imagery, dissolved-gas analysis (GDA), PD sensors, vibration, and environmental data to forecast initial faults and remaining useful life. Recent studies across energy systems and industries suggest that AI-enabled Predictive Maintenance (PdM) ensures data quality and effective model governance by lowering downtime and prioritizing work orders by risk [46].

The driving force behind ML success in PdM in power systems consists of core AI building blocks. These core AI blocks can broadly be categorized into (i) techniques utilizing signal processing and selected features. For instance, signal processing and selected features have played a vital role in transformers and breakers. Feature sets such as gas ratios, key-gas trends, temperature gradients, oil moisture, and trip-coil current waveforms can easily be engineered with time-frequency analysis [47]. (ii) Learning paradigms: methodologies relying on classical classifiers such as XGBoost, support vector machines (SVM), and random forest, which are still competitive on tabular sensor data, deep learning models including CNN, and transformers for images, that is, visual inspection or Infra-red images of grid systems, and multimodal fusion techniques and hybrids that take advantage of physics-based digital twins with data-driven residuals [48]. (iii) Edge/IoT Integration: utilization of data from low-power sensors, which can stream grid components' health to cloud platforms where DL models can provide real-time analytics for field workers.

4.1.1 But, what makes grid PdM distinct?

Like many other fields, grid PdM suffers from sparse labels and class imbalance. Robust machine/deep learning requires balanced data, while true failures are often rare in grids, thus, requiring cost-sensitive losses, resampling, and domain-informed labeling. The second key element is the environment. Many times in harsh environments, climate and seasonal changes degrade model calibration. The grids, therefore, require continuous monitoring and recalibrations. Large grids often consist of heterogeneous assets, including transformers, reclosers, and cables, which have different failure patterns and physics. For effective PdM, assets must encode installation context and loading history for ML models to generalize on the data [49].

Advancements in grid equipment Advancements in grip equipment can be observed in three key categories:

¹ A SCADA system is the digital nervous system of any modern power grids and industrial plants, which collects real-time data from sensors and controls across the grid.

1. Transformers (power and distribution): In transformers, multi-model ML techniques have replaced fixed ratio rules for DGA interpretations. ML techniques provide optimal operating conditions combining and analyzing thermal profiles, oil chemistry, and load data to predict insulation conditions, for instance [50].
2. Circuit breaker and switchgear: Recent studies have shown that improving maintenance planning, reducing operational costs, and enhancing the reliability of high-voltage circuit breakers using AI-integrated reliability-centered maintenance [51]. Additionally, many medium-voltage switchgears integrate novel sensors and MLR for e-mobility [52].
3. Digital twins: Digital replicas of physical systems are on the rise to detect system deviations and failures. Such systems utilizing data-driven or hybrid twins have proven useful in maintenance economics for grid systems [53].

4.2 Explainability and reliability of predictive models

The explainable AI for PdM for grid systems can be a vital tool for global transparency, local explanations, and symbolic surrogates with respect to grid systems. For instance, utilizing Shapley Additive exPlanations (SHAP) on grid failure predictions could highlight what drives risk across various assets within a system. Local interpretable model-agnostic explanations (LIME), on the other hand, are suited for tabular telemetry. LIME in PdM can tie an alarm to deviations in C_2H_2/C_2H_4 ratios, for instance. Hot-spot temperature can be mapped *via* saliency/Grad-CAM for infra-red in grid systems for explainability [54].

Although reliable, PdMs are not fault-proof. The operators must keep an eye on the red flags raised by a model. Maintenance planners need to know potential risks, not just the labels. It is imperative to monitor and manually cross-check vibration trends, ambient conditions, gas trend, etc., for the general safety of the grid system. It is also essential to segregate data noise from knowledge gaps, that is, sparse failure models, to decide whether there is a need for a retest or to collect more data for PdMs. Thus, there is a need for continuous performance tracking and regular drift tests for ML operation maintenance to ensure grid system reliability. A recent study suggests having a human-in-the-loop diagnostics [9, 54] for effective performance. Moreover, new studies place Trustworthy-AI governance for PdM in grid systems as a top priority [55]. It is to ensure the deployment of technical and organizational controls, which include robustness, data, quality, roles, audit, ethics—to name a few.

4.3 Case studies in PdM for grid equipment

This section lists a handful of case studies just to show the readers how ML and AI are deployed in various facets across grid systems. A case study is provided for each of the following equipment categories, that is, power transformers, circuit breakers, and beyond single assets (digital twins):

4.3.1 Case study 1: Power transformers—Overload alarm prediction in distribution transformers

Transformers are considered the backbone of any grid system, providing power to residential, commercial, and industrial units. Due to the high demand for power

consumption, coupled with the rapid growth of electric vehicles, transformers are often overloaded. Overloaded transformers pose greater risks to insulation aging and reducing lifetime, and can lead to winding temperature rise. This can also result in power failures. Many grids have “dumb” distribution transformers, meaning they have very basic sensors to no sensors at all. The lack of sensory data poses many challenges in correctly deploying models for overload alarm predictions. These challenges can be linked to the following:

- Data quality and availability
- Class imbalance
- Nonlinear thermal dynamics
- Heterogeneity of assets and environments, and
- Uncertainty in external factors such as ambient conditions and uncontrollable demand spikes

A data-driven predictive framework can be deployed to overcome these challenges [56].

4.3.2 Case study 2: Circuit breakers: AI-enhanced reliability-centered maintenance (RCM)

A key component of any grid system is the high-voltage circuit breakers (HVCBs), a protection device in transmission networks. HVCBs ensure the grid’s stability by protecting equipment and isolating faults within the networks. A single damaged HVCB may jeopardize the equipment’s safety. There are two types of maintenance these circuits require: (a) time-based maintenance (TBM) and (b) corrective maintenance. These can be costly and may pose a high risk exposure. Reliability-centered maintenance (RCM) provides one solution.

The challenges associated with RCM are as follows:

- High-dimensional and noisy data
- Complex degradation mechanisms, as failure can come from any component
- Operational diversity
- Limited labeled failure data, and
- Explainability and trust, that is, a black box alert is insufficient for high-risk assets.

A recent study by Hedayatnia et al. [51] has proposed AI frameworks to effectively address these challenges.

Beyond single assets—Twin-driven PdM Power grids consist of assets that operate under varying conditions. The classical PdM, as for instance discussed above, relies either on pure data-driven models or on physics models. These can drift when

conditions shift. Digital twin (DT) can ensure systems' reliability and stability under such conditions. A DT is a digital replica of a physical entity. They can act as early failure warnings when the difference between simulated states (DT) and sensor measurements deviates from a certain threshold. The challenges associated with this include the following:

- Model fidelity vs. real-world complexity
- Data integration and interoperability
- Synchronization and parameter drift
- Uncertainty quantification
- Scalability and compute cost
- Validation and operator trust

Recent studies have shown the effectiveness of DT-driven PdM for early warnings in Refs. [48, 53].

5. Conclusion

As ML becomes essential for analyzing smart grid data, addressing trustful AI is vital to ensure grid data justice and equitable access to smart grid services. To achieve this, ethical AI principles must guide development and deployment, aligning technology with societal values and public trust. Furthermore, bias needs to be detected and mitigated to ensure fairness and reliability in smart grid management systems. Moreover, explainable AI is needed to provide transparency, allowing stakeholders to understand and validate decisions. When designed with these principles, AI can become a trustful tool to help stakeholders or partner in decision-making, enhancing efficiency, resilience, and equity in future smart grid operations.

However, it has been pointed out by researchers that a smart grid should be an intelligent network of electricity that integrates the actions of all stakeholders, including generators, consumers, and one who does both, in order to supply electricity with effectiveness, environmental responsibility, economy, and security [8]. This should be further addressed in future by involving more rolls into the action—regulators, grid operators, technology providers, and consumers each have roles to play in ensuring that AI is introduced in a way that is both innovative and responsible. Moreover, as noted in Ref. [3] that regulatory barriers exist and are closely interlinked with technological challenges. Many technical solutions, such as privacy-preserving data analytics, interoperable systems, and explainable AI algorithms, are being driven by the need to comply with or satisfy regulatory demands [57]. In turn, overcoming these challenges enables stakeholders to unlock the multi-faceted benefits of smart grid AI.

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Section 2

Data-Driven Intelligence and Forecasting in Smart Grids

Machine Learning-Driven Stacked Ensemble Meta-Learning for Short-Term Solar Power Forecasting

Arif Hussain and Gelli Ravikumar

Abstract

This chapter presents an advanced short-term solar power forecasting method utilizing a machine learning-driven stacked ensemble meta-learning (ML-SEML) framework. The inherent intermittency of solar power poses a significant challenge to accurate forecasting, as traditional machine and deep learning models struggle to capture these fluctuations effectively. To address this issue, we propose a hybrid approach that integrates multiple canonical and ensemble models, including K-Nearest Neighbors (KNN), Multi-Layer Perceptron (MLP), Support Vector Regression (SVR), Gradient Boosting Regressor (GB), and Extreme Gradient Boosting (XGB) within a meta-learning framework. Real-world solar datasets are used to validate the proposed model's performance using key evaluation metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2) score. Comparative experiments demonstrate that the ML-SEML model consistently outperforms individual learning models and LSTM-based approaches, offering superior resilience, adaptability, and accuracy in forecasting complex solar power patterns. This chapter will provide insights into the design, implementation, and evaluation of ensemble-based forecasting techniques, contributing to enhanced solar energy integration and grid reliability.

Keywords: solar power forecasting, stacked ensemble, meta-learning, prediction, accuracy, model robustness

1. Introduction

Renewable energy (RE) is the need of the day, and clean energy has become the most focused target globally in recent decades. This need and focus of RE in the power market is the limited nature of conventional energy sources such as oil, gas, coal, etc. RE has the advantages of zero fuel costs, low operational and maintenance costs, and low emissions [1]. There are several RE resources like solar, wind, biomass, hydro, etc., among which wind and solar are the most commonly used [2]. The share of solar within the global energy mix reached 5.5%, up from 4.6% in 2022, according to

Ember [3]. Solar energy contributes to reducing global warming and environmental degradation because it emits no greenhouse gases and is also the most suitable RE source with its efficiency, affordability, and abundance.

However, the intermittent nature of solar energy introduces risks and challenges for its utilization as a base load in power systems. The power produced by solar energy systems varies with atmospheric conditions and solar irradiance. Unexpected fluctuations in solar power generation can increase the operational costs of electricity and pose significant risks to the reliability of the electricity supply. Various energy storage systems and complementary generation methods are used to meet the required demand and mitigate the intermittency of solar energy [4]. Integrating solar power into the grid can present several technical issues, such as voltage fluctuations, unintentional islanding, impacts on grid frequency, and power fluctuations within the grid. Several methods exist to address the intermittent nature of solar energy, including various smoothing approaches, control strategies, and accurate solar power forecasting (SPF). The initial and critical solution for managing the intermittency of solar energy is an accurate SPF.

Researchers and industry professionals have developed various SPF solutions to solve these issues; these can be broadly classified as hybrid, data-driven, or physical. These algorithms use a range of input features, such as historical power generation statistics, sun irradiance measurements, and meteorological data, to predict the output of solar PV systems [5]. In the past decade, data-driven machine learning (ML) and deep learning (DL) models have attracted much attention. Ensemble forecasting models are important in ML/DL forecasting tactics because they mix many models and forecast by averaging their results. Averaging forecasts helps reduce server biases when weather data contains outliers, preventing it from making the worst predictions [6]. Multiple methods have been published in the literature employing basic machines and deep learning models, such as KNN, SVR, MLP, GB, LSTM, and CNN [7, 8]. Traditional methods, on the other hand, frequently rely on a single model or basic combinations, making it challenging to capture complicated data patterns and anomalies.

In [9], the author proposes a stacking ensemble method using a recurrent neural network (RNN) as a meta-learner for short-term photovoltaic (PV) power forecasting. This approach combines five models—ANN, DNN, SVR, LSTM, and CNN—and achieves a mean relative error (MRE) of 4.29%, outperforming single models and a benchmark forest ensemble. Similarly, [10] presents a day-ahead PV power forecasting model using residual networks (ResNet) and dense convolutional networks (DenseNet) with meta-learning, though these models are computationally intensive and complex. While methods like stacking ensembles with RNNs or using ResNet and DenseNet models improve accuracy, they come with significant computational complexity due to the need for extensive training and tuning of multiple deep-learning architectures, making them less practical for real-time or large-scale applications.

To overcome this limitation, we present a stacked ensemble meta-learning model for SPF that leverages the capabilities of numerous canonical and ensemble learning models inside a single meta-learning framework. Traditional SPF methods rely on a single model, which can struggle to capture the complex, nonlinear patterns in solar power generation data. By incorporating a diverse set of canonical and ensemble models and utilizing LR as the meta-model, the ML-SEML model offers superior predictive accuracy and robustness. By combining these models into a stacked ensemble architecture, the ML-SEML model can easily manage the irregular and intermittent

nature of solar power data. The meta-model combines the specific characteristics of each base model to generate more accurate estimates. Our proposed framework includes the following contributions:

- We propose a stacked ensemble model (ML-SEML) to enhance prediction reliability by combining multiple base models, each addressing different data characteristics.
- The diverse models in ML-SEML ensure adaptability to varying features and dynamics of solar power generation, providing robustness against fluctuations.
- The proposed model achieves significantly lower MSE and MAE than LSTM and traditional methods, showcasing superior predictive accuracy.
- The proposed model reduces the influence of outliers while being computationally more efficient than LSTM, leading to faster training times and lower resource usage.

2. Methodology

The necessity to capture many facets of the underlying patterns in the data and improve prediction accuracy by using various learning methods motivated the selection of models for our proposed framework. For short-term associations in time-series data, KNN was selected due to its ease of use and efficiency in collecting local data structures. MLP, a fully linked feedforward neural network, is incorporated to simulate intricate non-linear interactions. SVR is appropriate for time-series forecasting with noise since it manages high-dimensional feature spaces well and reduces overfitting. The potent ensemble techniques GB and XGB make high prediction accuracy possible, which combines several weak learners to create strong models. XGB, in particular, is renowned for its effectiveness and capacity to manage intricate patterns and missing data. By integrating different viewpoints from basic and complicated models, we can improve generalization by utilizing the strengths of each model when we include them in a meta-learning framework.

2.1 KNN regressor

A popular instance-based lazy learning classification algorithm, the KNN technique aims to classify test instances according to how closely they resemble a set of k class centers in terms of their characteristics [11]. The key steps in utilizing the KNN algorithm to estimate probabilistic wind speed or power can be summarized as follows:

- Establishing a predetermined gap between the testing and training examples.
- Choosing K nearest neighbors from the training samples with the k lowest distances.
- Using an average approach to predict wind speed or power output.

Euclidean distance, the most widely used method, was employed using the eq. (1):

$$D_{(X,Y)} = \sqrt{\sum_{i=1}^n (x_i + y_i)^2} \quad (1)$$

where X and Y are two instances from the training and testing datasets, respectively; x_i and y_i are input variables, and n is the number of input variables.

2.2 MLP regressor

In 1958, Frank Rosenblatt, the original perceptron creator, built it as a device rather than an algorithm. The perceptron creates a single output that is reliant on numerous actual inputs using a linear combination of input weights [12]. They can be expressed mathematically using eq. (2).

$$y = \varphi \left(\sum_{i=1}^n w_i x_i + b \right) \Rightarrow \varphi(w^T x + b) \quad (2)$$

where w is the weight vector, x is the input vector, b is the bias, and φ is the nonlinear activation function. An MLP's major flaw is overfitting, which is handled by dividing data into training and validation sets. The phases in the perceptron learning process are as follows:

- Measure the total of the inputs after increasing them by a given weight.
- Multiply by the weight, then add a bias factor (0–1).
- Get the perceptron output by feeding the sum via the activation function.

2.3 SVR regressor

SVRs, introduced by Vapnik and colleagues, are unquestionably one of the most popular classification methods [13, 14]. SVR is a supervised method for classification and regression problems that uses hyperplanes to differentiate one data set from another in classification tasks. The weighted sum of training and bias outcomes is a class decision function connected with a hyperplane using eq. (3).

$$y(x) = w^T \varphi(x_n) + b \quad (3)$$

where w is the normal hyperplane weight vector, bias is represented by b , and x_n is a true dimensional function vector.

2.4 GB regressor

A powerful ensemble learning technique for regression and classification problems is gradient boosting (GB). GB, which Jerome Friedman developed in 1999,

builds models one after the other, aiming to correct the errors of the previous models [15]. The key benefit of GB is that it can create extremely accurate models due to its durability and versatility. It is possible to balance bias and variance and lower the likelihood of overfitting by carefully regulating the learning rate and the number of iterations. Eq. (4) represents the GB algorithm.

$$F_m(x) = F_{m-1}(x) + \eta h_m(x) \quad (4)$$

where: $F_m(x)$ is the current model, $F_{m-1}(x)$ is the previous model, η is the learning rate, $h_m(x)$ is the new base learner trained on the residual errors.

2.5 XGB regressor

Chen and Carlos improved GB in 2016 to increase performance using innovative optimization methods called Extreme GB [16]. Because of its precision, scalability, and versatility in regression and classification, it has emerged as one of the most used machine learning algorithms. XGB algorithm's key advantages are its capacity to handle complicated data connections, regularization approaches to minimize overfitting, and parallel processing for efficient calculation.

In each iteration, XGB minimizes a regularized objective function for eq. (4) that includes both the loss function and a penalty for model complexity. This objective function is given by:

$$\mathcal{L}(F) = \sum_{i=1}^n \ell(y_i, \hat{y}_i) + \sum_{k=1}^K \Omega(h_k) \quad (5)$$

where $\ell(y_i, \hat{y}_i)$ is the loss function (e.g., mean squared error) for the prediction y_i , $\Omega(h_k)$ is the regularization term for the k -th tree, which helps control overfitting.

2.6 Proposed ML-SEML model

There are various methods in ensemble learning for utilizing multiple models, including bagging, boosting, and stacking. In our proposed research, we utilize a stacked ensemble where the model combines the predictions of multiple base models using a meta-model, which learns optimally based on the weights of the base model. The definition of meta-learning is "learning to learn," which means that in meta-learning, a meta-model is trained to learn from the output of multiple base models [17]. The strength of individual models makes the stacked ensemble model more robust and accurate for forecasting. In our proposed ML-SEML model, we utilize canonical and ensemble models as base models, which include KNN, MLP, SVR, GB, and XGB, while for the meta-model, we utilize LR. By combining the predictions of these models using the meta-learning LR model, we can improve the accuracy and robustness of SPF. The meta-model uses the base models' predictions as input features to produce the final prediction. This method enables the meta-model to capture intricate interactions between the base models' predictions, perhaps leading to better performance.

Mathematically, let $\{M_1, M_2, \dots, M_k\}$ represent the base models. The prediction of the i -th base model for an input x is $y_i = M_i(x)$. The meta-model M_{meta} then takes the predictions $\{\hat{y}_1, \hat{y}_2, \dots, \hat{y}_k\}$ as input and produces the final prediction:

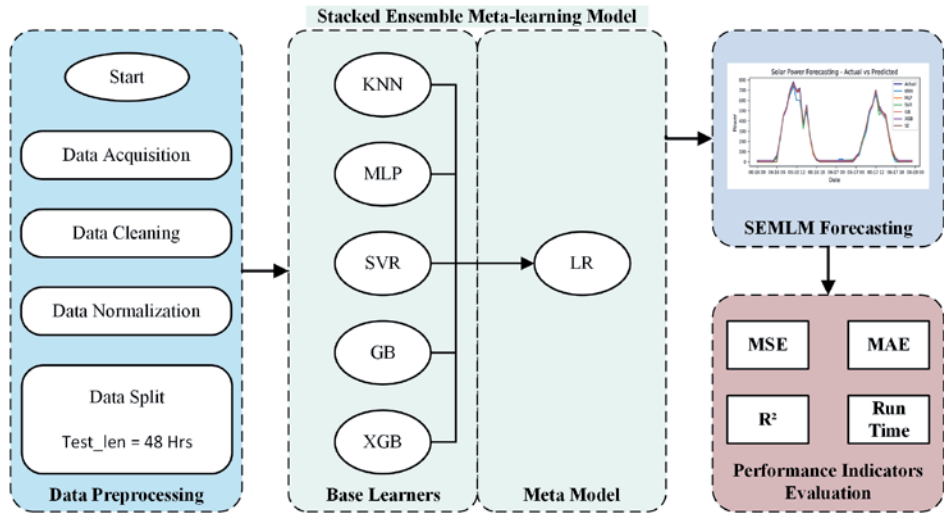


Figure 1.
Flowchart of proposed ML-SEML model.

$$\hat{y} = M_{\text{meta}} \left(\hat{y}_1, \hat{y}_2, \dots, \hat{y}_k \right) \quad (6)$$

For Linear Regression as the meta-model:

$$\hat{y}_j = \beta_0 + \sum_{i=1}^k \beta_i \hat{y}_{i,j} \quad (7)$$

The proposed ML-SEML model is divided into five segments, as illustrated in the flowchart in **Figure 1**. Initially, data preprocessing was carried out, including data acquisition, cleaning, normalization, and data splitting. In the second step, we have a layer of base models, including KNN, MLP, SVR, GB, and XGB. The output of base models is combined using the meta-learner LR model in the third step. In the fourth step, the forecasting is performed based on the ML-SEML model, and finally, the model is evaluated using evaluation metrics.

3. Case study

3.1 Data description

We analyzed data from a solar power plant in India during 34 days [18]. It consists of two file pairs, each including one power generation dataset and one weather sensor reading dataset. Power generation statistics are acquired at the inverter level, with each inverter connected to many lines of solar panels. Sensor data is collected at the plant level, and a single array of sensors is strategically positioned. The data include ambient and module temperature, irradiation, AC and DC power, daily and total yield, and the number of source keys. A correlation is a statistical term that reflects the degree of the link between two variables in terms of positive and

negative correlations. Correlation can be utilized to test theories regarding the causes and effects of relationships between variables, as shown in **Figure 2**. The seasonal decomposition of DC power is also shown in **Figure 3**, in terms of trend, seasonal component, and random residuals.

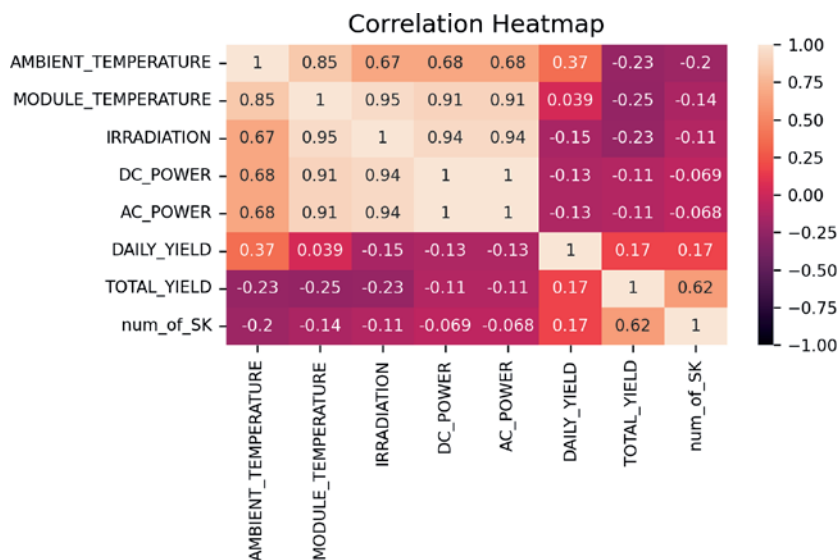


Figure 2.
Correlation matrix between variables of solar data.

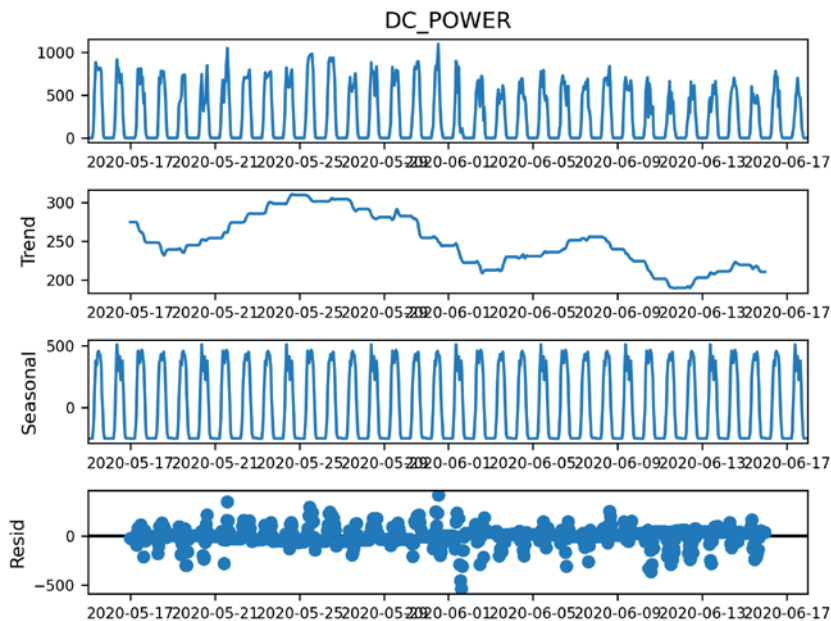


Figure 3.
Seasonal decomposition of DC power.

3.2 Evaluation metrics

Evaluate the performance of the ensemble meta-learning model on the testing data. The performance metrics used include MSE, MAE, the R^2 , and run-time, which are mathematically presented below.

$$MSE = \frac{1}{n} \sum_{j=1}^n \left(y_j - \hat{y}_j \right)^2 \quad (8)$$

$$MAE = \frac{1}{n} \sum_{j=1}^n \left| y_j - \hat{y}_j \right| \quad (9)$$

$$R^2 = 1 - \frac{\sum_{j=1}^n \left(y_j - \hat{y}_j \right)^2}{\sum_{j=1}^n \left(y_j - \bar{y} \right)^2} \quad (10)$$

where y_j is the actual value, $\hat{y}_j$ is the predicted value, and $\bar{y}$ is the mean of the actual values.

4. Results and discussion

In this work, we compared the effectiveness of various machine-learning models for solar power forecasting. The base models were KNN, MLP, SVR, GB, and XGB, compared with the proposed ML-SEML model, with LR as the meta-model. The key statistic utilized for comparison was the MSE; in **Figure 4**, we can see that the ML-SEML model has the lowest MSE compared to all other base models, while KNN has the worst MSE. To further examine the performance of our models, we created box plots of the predictions provided by each model

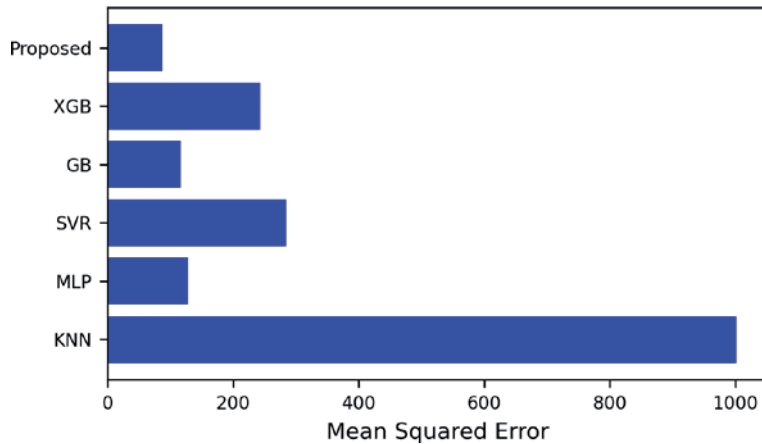


Figure 4.
Comparison of proposed ML-SEML model vs. base models.

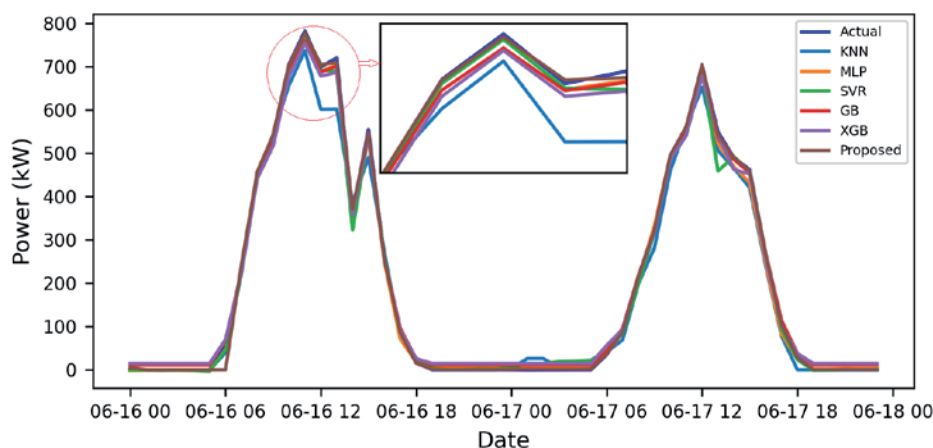


Figure 5.
Solar power forecasting: actual vs. predicted.

and compared them to the actual power values. **Figure 5** depicts a time series of actual and expected solar power levels over 2 days. The graphic shows predictions from both the basic models and the ML-SEML model. The zoomed graph clearly illustrates that ML-SEML model projections are more consistent with real power values, especially during periods of significant fluctuation. This highlights the ML-SEML model's capacity to detect complex patterns and trends in solar power data, which leads to more precise forecasts.

The comparison between our proposed ML-SEML model, base models and the LSTM are summarized in **Table 1**. The proposed model demonstrates superior performance compared to base and LSTM models. With an MSE of 87.25 and MAE of 3.73, the proposed model significantly outperforms LSTM, which has a higher MSE of 265.84 and MAE of 10.97. Additionally, ML-SEML achieves a near-perfect R^2 of 0.999, showcasing its robustness in predictive accuracy, while LSTM lags with an R^2 of 0.995. Furthermore, ML-SEML's runtime of 0.01559 mins is three times faster than LSTM's 0.0483 mins, making it computationally more efficient, thus highlighting its overall dominance.

Models	Performance Indices			
	MSE	MAE	R^2	Run Time
KNN	1001.61	18.79	0.985	0.0003
MLP	128.14	7.53	0.998	0.0096
SVR	284.53	8.97	0.995	0.0011
GB	116.73	9.95	0.998	0.00011
XGB	243.02	13.87	0.996	0.0003
LSTM	265.84	10.97	0.995	0.0483
ML-SEML	87.25	3.73	0.999	0.01559

Table 1.
The comparison between proposed ML-SEML, base models, and LSTM.

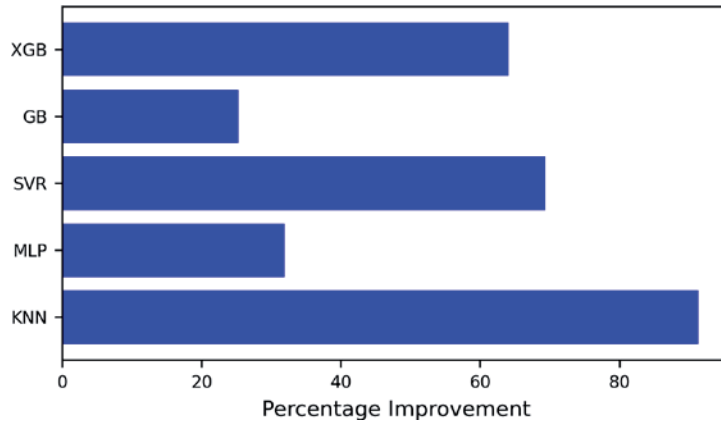


Figure 6.
Percentage improvement of proposed ML-SEML model over base models.

In the final analysis, we determined the MSE-based percentage improvement of the ML-SEML model over each of the base models. The improvements are shown in a bar chart in **Figure 6**. The percentage improvement is computed using the following formula:

$$\text{Improvement} = \left(\frac{MSE_{\text{base}} - MSE_{\text{meta}}}{MSE_{\text{base}}} \right) \times 100 \quad (11)$$

The findings further demonstrate the ML-SEML model's usefulness for SPF by showing that it significantly improves upon base models overall. To sum up, the findings show that our proposed stacked ensemble meta-learning (ML-SEML) model performs much better on all performance measures and routinely beats conventional base models in terms of MSE, MAE, and R^2 . It also produces more accurate and dependable predictions.

While the proposed ML-SEML model was evaluated using a specific solar dataset, we acknowledge the need to assess its robustness across various seasonal and geographical contexts rigorously. Variations in solar irradiance, which can arise from factors such as local climate conditions, topographical features, and seasonal fluctuations, can significantly affect the accuracy of solar forecasting. To address this, future research will validate the model using datasets from regions with differing climates, including tropical, temperate, and arid environments. Additionally, we intend to incorporate data that reflects diverse terrain types, such as urban areas, mountainous regions, and open plains, to ensure that our model achieves high generalization and real-world applicability across multiple scenarios. This comprehensive approach aims to enhance the model's predictive capabilities and reliability in practical applications within the solar energy sector.

5. Limitations and practical considerations

The proposed ML-SEML model performs well in short-term solar power forecasting; nonetheless, it is crucial to recognize some limitations. One noticeable limitation

is the model's sensitivity to hyperparameter adjustment, which can considerably impact performance. While we used cross-validation to verify the model's resilience, using hyperparameter optimization approaches like grid search or random search might improve the model's efficiency and accuracy. Furthermore, there is a risk of overfitting, especially when dealing with correlated features in training data. To overcome this issue, we focused on data pretreatment approaches and used cross-validation to reduce overfitting. However, future studies might look at feature selection or regularization approaches to reduce overfitting, particularly when applying the model to larger and more complex datasets.

The proposed ML-SEML model was implemented using Python 3.8. Scikit-learn is used for machine learning methods (KNN, MLP, SVR, Gradient Boosting, and XGBoost), NumPy and Pandas for data processing, and Matplotlib and Seaborn for data visualization. The TensorFlow and Keras libraries (tensorflow.keras.models.Sequential and tensorflow.keras.layers.LSTM, Dense) were used to compare LSTM-based models. Model training and assessment were performed on a conventional workstation without GPU acceleration. The stacking ensemble was built with Scikit-learn's StackingRegressor framework. To guarantee repeatability, random seeds were set throughout training. The workflow consisted of data preprocessing (scaling and normalization), base model training, prediction generation from base models, and final prediction using the meta-learner.

Real-world implementation in grid operations requires careful consideration of a number of realistic issues. First, latency is a crucial consideration. The suggested ML-SEML framework offers good forecasting accuracy, but there may be a little computational burden due to its multi-model design. However, the delay stays within reasonable bounds for integration into energy management systems (EMS) because the model works on short-term forecasting horizons (e.g., 15 minutes to 1 hour ahead). Integrating with the current grid infrastructure presents another difficulty. A real-time data pipeline that can process high-frequency solar irradiance and power measurements must incorporate the forecasting model. Additional data formatting or middleware development may be necessary to ensure compatibility with Distributed Energy Resource Management Systems (DERMS) or Supervisory Control and Data Acquisition (SCADA) systems.

In this study, we employed fundamental feature engineering techniques, such as normalization and the construction of lag features, to effectively capture the temporal dependencies inherent in solar irradiance patterns. Normalization was utilized to scale the data, ensuring that all features contribute equally to the learning process, while lag feature creation helped in encoding past values and trends, which are critical for predicting future irradiance levels. These strategies aimed not only to enhance the predictive accuracy of our models but also to minimize noise that can obscure meaningful patterns in the data. Although we did not incorporate advanced dimensionality reduction techniques such as Principal Component Analysis (PCA), t-distributed Stochastic Neighbor Embedding (t-SNE), and autoencoders in the current analysis, we recognize their significant potential for future research. These techniques can play a vital role in managing high-dimensional sensor data by reducing redundancy and computational overhead, allowing for more efficient processing and potentially improved model performance. By applying these methods, future studies could uncover deeper insights and facilitate a more streamlined analysis of complex datasets related to solar energy.

Future work will concentrate on overcoming these problems and refining the ML-SEML framework for smooth deployment in operational contexts.

6. Conclusion

In this research, we proposed a machine learning-driven stacked ensemble meta-learning model for solar power forecasting, using KNN, MLP, SVR, GB, and XGB as base models and LR as the meta-model. The ML-SEML model outperformed individual base models and the LSTM model regarding MSE, MAE, R^2 , and runtime. The results demonstrated the ML-SEML model's capacity to detect complex patterns and temporal dynamics in solar power data, resulting in more accurate and dependable forecasts than standard models. The box plots and time series graphs demonstrated the ML-SEML model's ability to predict solar power with low variation and greater faithfulness to absolute power levels. Furthermore, the ML-SEML model achieved significant percentage gains over the base models and the LSTM, demonstrating its usefulness in improving solar power forecasting accuracy. The proposed model can predict any of the variables shown in **Figure 2**. Future research should incorporate real-time meteorological data for improved accuracy and develop hybrid models that combine the ML-SEML model with RNNs or LSTMs to ensure scalability and resilience under different conditions.

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Conflict of interest

The authors declare no conflict of interest.

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Section 3

Advanced Control and Power Management of Microgrids

Advanced Power Management in Renewable Energy Microgrids

Fei Deng

Abstract

This chapter illustrates the power management issues in renewable energy microgrids. Firstly, the system structure and operation modes of renewable energy microgrids are presented. On this basis, the power management issues in both grid-connected and islanded microgrids are discussed. In grid-connected microgrids, the key point is suppressing the negative effect from the load side. In steady states, when unbalanced and nonlinear loads are supplied, the unbalanced and harmonic components in grid current are eliminated to improve grid power quality. On the other hand, inertia emulation is implemented in the controller of power converters in microgrids to ease the impact of load disturbance on grid frequency, and it can be realized *via* capacitors at the DC side of grid-tied inverters, DC-side distributed generation units, and other methods (e.g., smart loads). As for the power management in islanded microgrids, the essential target is eliminating the impact of mismatched feeder impedances and then achieving equal/proportional power sharing between parallel distributed generation units. Generally, power droop control can be designed based on feeder impedance characteristics, and the adaptive virtual impedance regulation is also effective in realizing accurate power sharing. After that, the future trends in this field are predicted, and the power management in renewable energy microgrids faces the challenge of new power converter functions and coordination with multiple control targets. Meanwhile, emerging techniques, for example, digital twins, virtual power plants, and artificial intelligence, are effective in improving the power management performance in microgrids.

Keywords: renewable energy, distributed generation units, microgrids, power management, adaptive virtual impedance

1. Introduction

In past decades, with the rapid development of the industry, the energy demand has been surging. Meanwhile, global production activities still rely heavily on fossil fuels, for example, coal, oil, and natural gas. However, fossil fuels are finite resources formed over millions of years and they may deplete in the near future. On the other hand, burning fuel also produces greenhouse gas emissions, for example, CO₂, N₂O, and SO₂ which contribute to global warming and climate change, and consequently threaten human daily life in return [1].

To address the above-mentioned problems, countries all over the world are committed to implementing diverse policies and setting targets to achieve net-zero greenhouse gas emissions, aiming to mitigate climate change and promote sustainable development. In 2019, the European Union launched the European Green Deal to make Europe the first climate-neutral continent by 2050 [2]. In China, it was announced in 2020 that China will peak carbon emissions before 2030 and aims to achieve carbon neutrality by 2060 [3]. The USA has set a target to cut emissions by 50 ~ 52% by 2030 (compared to 2005 levels) and to reach net-zero emissions by 2050 [4]. In all the roadmaps, a key point is that power generation with renewable energy sources (RESs), for example, wind turbines and photovoltaic (PV), is a promising solution to net-zero greenhouse gas emissions [5]. RESs generate electricity power by harnessing natural energy sources from the earth. Wind turbines convert kinetic energy from wind into electricity with generators, and PV arrays harvest solar energy and then transform it into electricity. Unlike fossil fuels, RESs do not consume limited energy sources and therefore do not generate greenhouse gas emissions as well; they contribute to sustainable power generation [6].

To ensure the sufficient power generation of RESs, the plants are always placed in locations with rich natural energy sources (e.g., sunlight and wind), which limits the availability of RESs. Furthermore, RESs' generation relies on weather conditions. As a result, their powers cannot remain consistent and are intermittent: Solar power is only available during the day or in sunny weather, and wind power depends on wind speeds. Directly connecting RESs to existing utility grids may cause significant random energy fluctuations, affecting the normal operation of the grid and even threatening its stability. On the other hand, when the utility grid fails, RESs must immediately shut down and exit the normal operating state, which greatly weakens the advantages of RESs. In order to integrate the benefits of RESs, mitigate their impact and negative effects on the grid, and ensure the quality of electricity supply to users, the concept of microgrids has emerged [7].

Microgrids are small-scale power generation and distribution systems, where RESs, energy conversion devices, electric storage systems, electric loads and corresponding system control, measurement, and protection equipment are involved [8]. They are controllable units that can operate independently to supply loads, and can also interconnect with the utility grid to balance power flow [9].

Although renewable energy microgrids are effective in suppressing greenhouse gas emissions, there are still substantial issues with their applications, such as the intermittency and variability of natural energy sources, and complex system integration of various RESs and energy storage systems. Besides, the cooperation of microgrids and utility grids may be threatened by stability issues. Furthermore, since RESs are always interfaced *via* power electronic converters, whose characteristics are significantly different from those of conventional synchronous generators, new challenges, for example, lack of inertia, are also introduced [10]. For these problems, the power management issues in renewable energy microgrids are analyzed in this chapter, and corresponding solutions are introduced accordingly.

2. Renewable energy microgrids

To realize zero-emission power generation, the concept of microgrid is proposed to integrate various distributed RESs. Since the power generation by RESs is based on renewable energies and no fossil fuel is burned, it saves natural resources and

suppresses environmental pollution. In this section, the system structure and operation modes of renewable energy microgrids are illustrated.

2.1 System structure

A typical renewable energy microgrid is depicted in **Figure 1**. It includes:

2.1.1 Distributed generation units (DGUs)

DGUs are the power generation sources to convert natural energy sources into electricity power, for example, wind turbines and PV arrays.

2.1.2 Power conversion devices

They are interfaces of DGUs in microgrids, facilitating the conversion between AC and DC power. Power conversion devices are always power electronic converters, and they can realize AC to DC conversion *via* rectifiers, DC to AC conversion *via* inverters, and power conversion between different DC voltage levels *via* DC-DC converters.

2.1.3 Energy storage systems (ESSs)

ESSs are employed as power buffers to suppress the impact of the intermittency and variability of natural energy sources, absorb surplus power from DGUs, and generate deficient power when the power generation from DGUs is insufficient *via* bidirectional power flow. The commonly used ESSs are batteries, ultracapacitors, and flywheels.

2.1.4 Electric loads

Electric loads refer to the devices and systems that consume electrical power; they can be residential household appliances, industrial electrical apparatus, and electric vehicles.

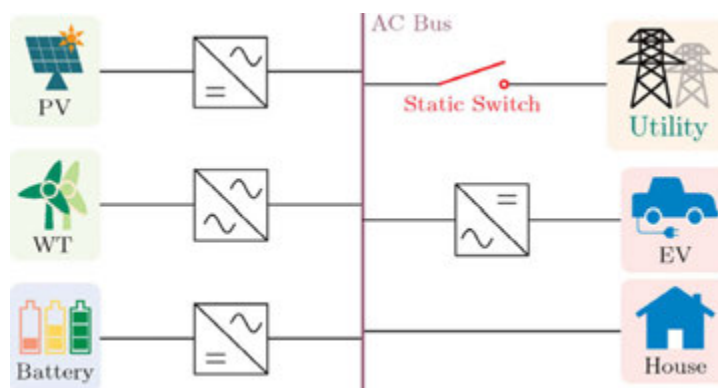


Figure 1.
 A typical renewable energy microgrid.

2.1.5 Static switch

It is located between the point of the common couple (PCC) of microgrids and utility grid, providing flexible operation of microgrids in both grid-connected and islanded modes.

Besides, there are some other essential devices to measure current and voltage signals, control power electronic converters, ensure system protections, and exchange information between DGUs *via* communication, consequently ensuring the efficient and reliable operation of microgrids.

2.2 Operation modes

Microgrids are flexible; they can operate in grid-connected mode to coordinate with the utility grid, and can also operate in islanded mode to independently supply load demand.

2.2.1 Grid-connected mode

Microgrids are in this operation mode when the static switch is closed. In this condition, the AC bus voltage is supported by the utility grid, and microgrids manipulate the power exchange with the utility grid.

2.2.2 Islanded mode

When the utility grid voltage or frequency is out of the normal range, or based on the preset operation schedule, microgrids will be disconnected from the utility grid and operate in islanded mode, independently supplying load demand. Therefore, the load voltage is formed by the DGUs in microgrids.

3. Power management issues in renewable energy microgrids

In renewable energy microgrids, various DGUs are involved; the integration of these DGUs requires efficient power management. Furthermore, when microgrids are in grid-connected mode, their operation may have negative effects on the utility grid, which will lead to blackout and result in significant economic losses [10]. On the other hand, in islanded microgrids, DGUs are parallel connected to form bus voltage and serve load demand; the inaccurate power distribution between DGUs degrades the system operation efficiency and reliability [11]. Therefore, the power management of renewable energy microgrids in both grid-connected and islanded modes must be considered.

4. Power management in grid-connected microgrids

In grid-connected microgrids, the AC bus voltage is supported by the utility grid, and parallel DGUs mainly manipulate the bidirectional power flow. In this condition, the primary power management target is minimizing the impact on the utility grid. Therefore, the stable operation of microgrids must be ensured first. On this basis, some advanced issues, such as power quality degradation caused by unbalanced and

nonlinear load, and inertia loss resulting from high penetration of RESs, also need to be addressed to ensure reliable and efficient operation of microgrids.

4.1 Power quality improvement

4.1.1 Power quality degradation

As seen in **Figure 2**, in grid-connected microgrids, various loads are supplied. When nonlinear loads, for example, data centers, telecom systems, and electric vehicle chargers, are included, the harmonic components will be involved in the load current, and they may be injected into the grid current, increasing total harmonic distortion (THD) in the utility grid and leading to excessive heating in transformers, cables, and generators. Likewise, when the single-phase loads are supplied, the power demand in three phases is unbalanced, which introduces unbalanced current components and creates unequal phase voltages at the point of common coupling. According to IEEE standard 519-2022 [12], the harmonic and unbalanced currents should be handled locally in microgrids as much as possible.

4.1.2 Power quality improvement strategies

To suppress the undesired components, for example, unbalanced and harmonic components, in the grid current, the grid-tied inverter absorbs these components in the load demand. To this end, in the controller of the grid-tied inverter, the grid current can be regulated, and the references for the undesired components are set as zero [13]. To eliminate certain current components, the resonators at these frequencies can be employed, and they are combined with proportional gain to form proportional-resonant controllers. Besides, when multiple harmonic components are involved in the load current, the number of resonators will increase dramatically,

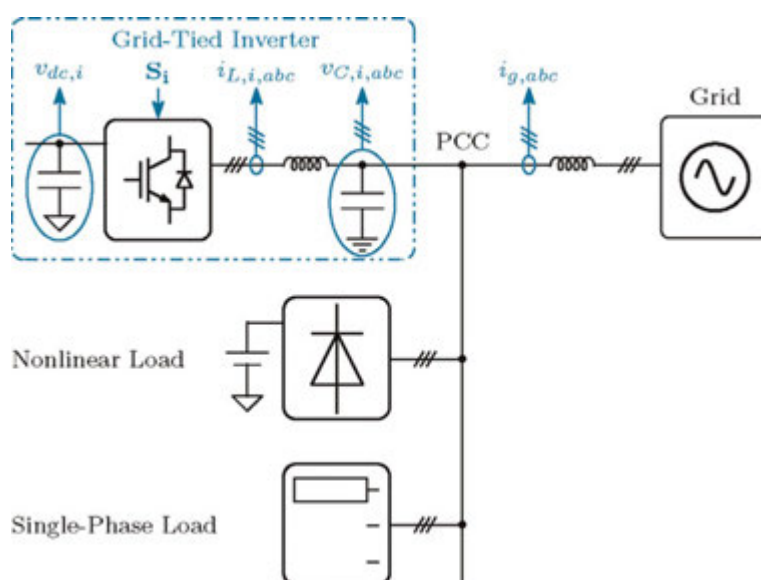


Figure 2.
 Power quality issue in grid-connected microgrids.

which makes the controller complicated and leads to a heavy calculation burden. In this case, repetitive control is a more effective tool.

4.1.2.1 Proportional-resonator control

Proportional-resonator (PR) control is a control strategy designed to provide infinite gain at a specific frequency, typically used in tracking sinusoidal reference signals or rejecting sinusoidal disturbances [14].

The standard expression of a PR controller is

$$G_{pr}(s) = k_{p,pr} + \frac{k_{r,pr}s}{s^2 + \omega^2} \quad (1)$$

where $k_{p,pr}$ and $k_{r,pr}$ are the proportional gain and resonant gain, respectively, ω is the central frequency.

From Eq. (1), it can be seen $G_{pr}(s)$ is infinite at $s = j\omega_0$. Consequently, the AC signal at this frequency will track its reference with steady-state zero. Setting grid current at ω_0 as zero, the corresponding grid current component will be eliminated.

Meanwhile, it is apparent that the controller in Eq. (1) is only effective for disturbance rejection at one certain frequency. When more than one AC disturbances are involved in load demand, multiple resonators are required, and the controller is modified as

$$G_{pr}(s) = k_{p,pr} + \sum_{n=\pm 1,3,5,\dots} \frac{k_{r,i,pr}s}{s^2 + (n\omega_0)^2} \quad (2)$$

where ω_0 is the fundamental frequency, $n = \pm 1, 3, 5, \dots$ is the harmonic order, whereas $n = 1$ and $n = -1$ indicate the fundamental positive-sequence and negative-sequence components, respectively.

On the other hand, the ideal resonator with infinite gain is underdamped, which may lead to the controlled plant unstable. Therefore, in practical implementations, the damping is always added. In this case, the controller mentioned in Eq. (2) is modified as [15].

$$G_{pr}(s) = k_{p,pr} + \sum_{n=\pm 1,3,5,\dots} \frac{k_{r,n,pr}s}{s^2 + 2\xi n\omega_0 s + (n\omega_0)^2} \quad (3)$$

where ξ is the damping factor.

With the increasing number of resonators, the calculation burden will increase dramatically, which makes the control algorithm difficult for the digital implementation. In this case, the repetitive control is more suitable.

4.1.2.2 Repetitive control

Repetitive control is a control strategy designed specifically to achieve high-accuracy tracking or disturbance rejection of periodic signals. It is particularly useful in systems that operate with periodic reference inputs or disturbances [16]. Besides, repetitive control is achieved by embedding a delay operator and a feedback loop that stores and uses the periodic behavior and corrects it in future cycles.

The general expression of repetitive control in the discrete domain is [17].

$$G_r(z) = \frac{\varepsilon}{1 - z^{-N}} \cdot Q(z) \tag{4}$$

where ε is the learning gain, N is the number of samples in the fundamental period, and $Q(z)$ is the low-pass filter to ensure robustness and reduce sensitivity to model mismatch or noise.

The controller mentioned in Eq. (4) acts like a memory buffer for one full period and compares past errors to adjust the present control action. Therefore, the unbalanced and harmonic components, whose frequencies are integral times of the fundamental frequency, can be effectively eliminated in the grid current. Compared to the PR controller, merely one controller is required to design, and the undesired grid current components decrease with each fundamental period. On the other hand, the rate of convergence with repetitive control is slower than that of PR controllers.

The comparison between PR control and repetitive control is presented in **Table 1**. In practical applications, the selection of the control scheme for power quality improvement should consider the load demand characteristic and controller design objectives. When the number of undesired current components is small, for example, when uncontrolled rectifiers are supplied, the dominated current components are 5th and 7th harmonics, and the PR controller can be employed. On the contrary, when substantial harmonics are involved in the load current, repetitive control is more suitable.

4.2 Inertia emulation

4.2.1 Inertia loss

In conventional power systems, power generation is mainly based on synchronous generators (SGs). Since SGs store kinetic energy in their rotating masses, when a disturbance (e.g., load demand change) occurs, the rotors buffer frequency changes to provide inertia, then allowing SGs to react. On the contrary, in modern microgrids, DGUs are interfaced *via* power electronic converters to realize various control missions in general cases. The operation of power electronic converters relies on fast-switching semiconductor devices that do not store kinetic energy, which is disabled to provide inherent inertia (seen in **Figure 3**) [18]. As a result, grid frequency changes rapidly when the generation or load disturbance occurs, threatening system stability

Strategies	Advantages	Disadvantages
PR control	Fast dynamic response	Merely effective at a certain frequency
	Simple controller design	Less effective for wideband harmonics
	Low computational burden	Imprecise digital implementation
Repetitive control	Effective for wideband harmonic	More complex implementation
	High accuracy	Slow convergence
	Internal model principle	Sensitive to frequency variation

Table 1.
Comparison between different control algorithms for power quality improvement.

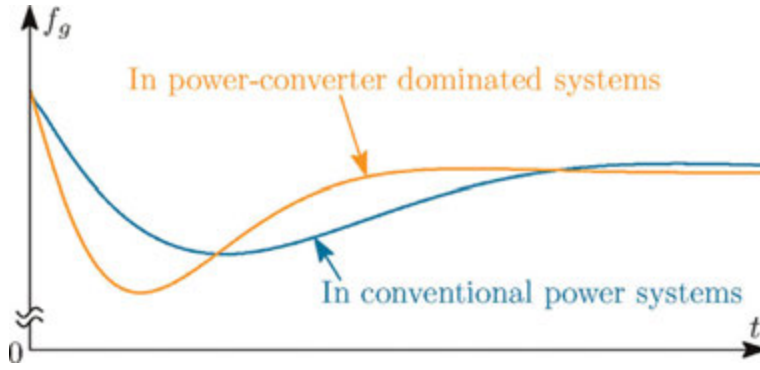


Figure 3.
Inertia loss in power-converter-dominated power systems.

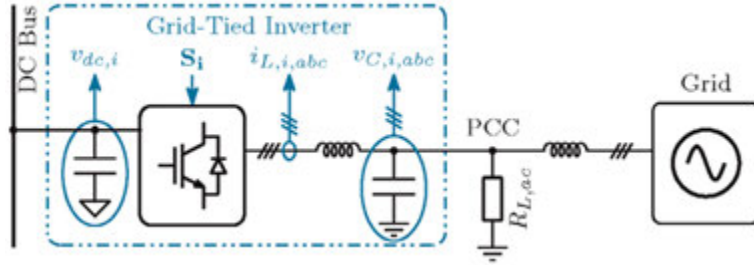


Figure 4.
System structure for capacitor-based inertia emulation.

and leading to undesired load shedding and even blackouts. To address this issue, inertia emulation can be implemented in the control algorithms of power converters.

4.2.2 Inertia emulation strategies

Since inertia is a dynamic characteristic of power systems, energy storage systems, for example, capacitors and batteries, are necessary for inertia emulation in renewable energy microgrids. If the load demand increases, the grid frequency will consequently decline. Then, the energy storage systems generate power to make up for the power deficiency from the grid. Likewise, the energy storage systems absorb surplus power when the load demand decreases.

According to the types of energy storage systems, the inertia emulation strategies can be sorted into capacitor-based and DGU-based methods.

4.2.2.1 Capacitor-based inertia emulation

As shown in **Figure 4**, in power electronic converters, capacitors are widely exploited in the input and output sides to filter high-frequency components in voltages and currents. Therefore, it is convenient to implement inertia emulation with capacitors.

Typically, the DC-link capacitor of grid-connected inverters can be employed to provide virtual inertia. In the work of Fang et al. [19], a proportional link is established between grid frequency f_g and DC-link voltage V_{dc} as

$$V_{dc} = V_{dc,N} + k_f \cdot (f_g - f_{g,0}) \quad (5)$$

where $V_{dc,N}$ and $f_{g,0}$ are the nominal values of dc-link voltage and grid frequency, respectively, k_f is the proportional gain.

From Eq. (5), it is revealed that when the grid frequency deviates from its nominal value, the DC-link voltage will deviate from the nominal voltage as well. That is, V_{dc} can be exploited to reflect f_g .

Meanwhile, the energy stored in the capacitor is expressed as

$$E_c = \frac{1}{2} C_{dc} V_{dc}^2 \quad (6)$$

where C_{dc} is the capacitance value.

It can be seen that the oscillation of V_{dc} changes the energy stored in the capacitor. Furthermore, based on Eqs. (5) and (6), the following relationship can be established: When f_g declines, V_{dc} will decrease proportionally, decreasing E_c . Consequently, the capacitor discharges to generate positive power, slowing down the frequency response. Similarly, when f_g increases, the capacitor will be charged to absorb the surplus power. Therefore, with this control algorithm, the grid frequency oscillation is eased by the DC-link capacitor.

However, from Eq. (5), it is inferred that the DC-link voltage varies with this strategy. In general cases, the DC-link voltage range is limited, restricting the provided transient power. Thus, the inertia emulated by the DC-link capacitor may be insufficient, especially when the system capacity is large.

4.2.2.2 DGU-based inertia emulation

In renewable energy microgrids, various DGUs are involved, and they can be exploited to provide virtual inertia [20]. Battery is a common solution. In the power system in **Figure 5**, the DC voltage regulation and virtual inertia are arranged to the battery module and the grid-tied inverter. In this case, the inertia emulation is implemented by generating transient power based on the rate of change of frequency (RoCoF) as

$$P_{vi} = -\frac{2H_b S_N}{f_{g,0}} \cdot \frac{df_g}{dt} \quad (7)$$

where H_b indicates the inertia constant provided by the battery, and S_N is system capacity.

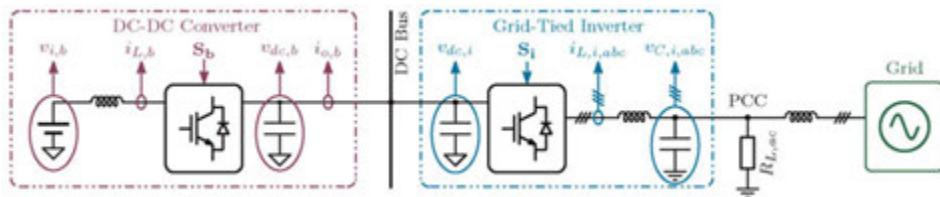


Figure 5.
 System structure for DGU-based inertia emulation.

Based on the function arrangement, there are two different schemes. The first one is that the battery regulates DC voltage, and the grid-tied inverter operates in power mode to provide virtual inertia. In this case, RoCoF can be estimated in the local controller of the grid-tied inverter, and the process in Eq. (7) is implemented as an outer loop to adjust the active power reference value. In this scheme, all the control targets are realized based on local information of power converters; no communication is required. The second one is that the grid-tied inverter regulates DC voltage, and the battery generates transient power. In this case, the grid frequency information should be transmitted from the grid side to the battery interface converter, which requires high-bandwidth communication, introducing an extra threat to system reliability and increasing cost. Thus, the first scheme is better than the second one.

Besides, other DGUs, for example, PV panels and wind turbines, can also be employed for inertia emulation. To exploit as much as possible the renewable energy, PV and wind turbine modules operate in Maximum Power Point Tracking (MPPT) mode. As a result, they can only generate negative transient power by removing the operating points from their maximum power points. To avoid this issue, these DGUs can operate in reserve power control mode, where their output power is set to be smaller than the maximum value [21]. In this case, both positive and negative transient power can be generated to provide virtual inertia.

Since the capacities of DGUs are much larger than that of DC-link capacitors, they can provide sufficient inertia to the power systems, without introducing extra hardware. However, DGUs have been arranged with other functions already, and when inertia emulation is arranged, the multiple functions may conflict with each other, the coordination between these functions should be considered, which complicates the controller design. Besides, when multiple DGUs are employed to provide virtual inertia, how to distribute the dynamic power between these DGUs is also another issue to consider.

4.2.2.3 Other inertia emulation methods

In the above two types of methods, inertia emulation is realized on the power source side. In the work of Qi et al. [22], a power electronics-interfaced smart load is designed to provide virtual inertia, where a transformerless electric spring topology and the associated control strategy have been developed to provide substantial inertia support from the noncritical load. However, this method requires extra hardware design.

Various inertia emulation solutions are compared in **Table 2**, and the suitable strategy can be selected based on the specifications and control objectives.

Energy storage systems	Advantages	Disadvantages
DC capacitors	Simple to implement fast response	DC voltage deviation Insufficient capacity
DGUs	Sufficient capacity, flexible arrangement	Trade-off with other functions, requires dynamic power distribution
Smart loads	Excellent voltage quality	Needs extra hardware design

Table 2.
Comparison between different control algorithms for inertia emulation.

5. Power management in islanded microgrids

When the static switch in **Figure 1** is released, the microgrid is isolated from the utility and operates in islanded mode. In this case, the AC voltage is formed by DGUs and the main power management issue is distributing power demand between parallel DGUs.

5.1 Feeder mismatch in islanded microgrids

In islanded microgrids, the dispatchable DGUs operate in voltage mode to form AC bus voltage. In ideal conditions, for the parallel dispatchable DGUs, the load power demand should be distributed proportionally according to the power ratings of DGUs. However, in real applications, the powers from DGUs are determined by the feeder impedance between DGUs and loads. Due to geographical restrictions, the DGUs and loads are located in different positions, and the feeder impedances responding to DGUs are mismatched with their power ratings [23]. As a result, some DGUs are overloaded and the other are in light-load conditions, which degrades the system safety and reduces the operation efficiency of DGUs.

Furthermore, like in grid-connected microgrids, unbalanced and nonlinear loads may be supplied in islanded microgrids. In this condition, not only active and reactive powers, but also unbalanced and harmonic powers must be distributed accurately between DGUs [24].

5.2 Power management strategies in islanded microgrids

Existing power management methods for islanded microgrids are mainly based on power droop control and adaptive virtual impedance regulation, and they are illustrated as follows:

5.2.1 Power droop control

Power droop control is widely used in islanded microgrids for power sharing among multiple DGUs. It mimics the behavior of traditional synchronous generators and enables autonomous power sharing without a communication network. According to the feeder impedance characteristics, the expression of power droop control is different [25].

Industrial power grids are medium- and high-voltage systems in general cases, where feeder lines exhibit higher inductance. In this condition, the power droop controllers are expressed as

$$\begin{cases} f = f_0 - k_{f,p} \cdot P \\ V = V_N - k_{v,q} \cdot Q \end{cases} \quad (8)$$

where f and V are the frequency and magnitude of AC voltage, f_0 and V_N are their nominal values, P and Q are active and reactive powers, $k_{f,p}$ and $k_{v,q}$ are droop gains, respectively.

In low-voltage microgrids, for example, residential microgrids, the feeder impedances are resistive-dominant. In such power systems, the relationship in Eq. (8) is not suitable anymore, and the droop control loops are modified as

$$\begin{cases} V = V_N - k_{v,p} \cdot P \\ f = f_0 + k_{f,q} \cdot Q \end{cases} \quad (9)$$

where $k_{v,p}$ and $k_{f,q}$ are droop gains, respectively.

In some cases, such as microgrids with long cables, the feeder impedances may include both inductive and resistive components. As a result, the active and reactive powers are coupled with each other, and the droop loops in Eqs. (8) and (9) are insufficient for power distribution. Consequently, the droop control loops are generalized as

$$\begin{cases} f = f_0 - k_{f,p} \cdot P - k_{f,q} \cdot Q \\ V = V_N - k_{v,p} \cdot P - k_{v,q} \cdot Q. \end{cases} \quad (10)$$

Note that, with the above three kinds of droop control loops, the magnitude and frequency of AC voltage will deviate from their nominal values, degrading voltage quality. Besides, since the frequency is a global variable, the power sharing realized *via* frequency droops is accurate. However, the output voltage magnitude is a local variable for each DGU; the power sharing based on voltage droops is degraded by feeder impedances. Furthermore, with power droop control, merely active and reactive power distribution is considered, and the unbalanced and harmonic power sharing requires extra droop loops at the corresponding frequencies, which complicates controller design and requires a large amount of computing resources.

5.2.2 Adaptive virtual impedance regulation (AVIR)

Another effective power management solution is based on virtual impedance. In this kind of method, the virtual impedances are inserted into be series with the original feeder impedances, suppressing and eliminating impedance mismatches [26]. Furthermore, to simultaneously ensure accurate power sharing and maintain bus voltage quality, the virtual impedance is adaptively regulated based on the current or power error as

$$Z_{vi}(s) = G_r(s)(X_i - X_i^*) \quad (11)$$

where $G_r(s)$ is the regulator, and it can be an integrator or a proportional-integral (PI) controller, X_i is the controlled variable, it can be active power, reactive power, harmonic power, current magnitude, or phase angle, and X_i^* is the reference value.

Since the integrator is involved in $G_r(s)$, the error between X_i and X_i^* can be effectively eliminated to ensure accurate power sharing.

Further, in general cases, $Z_{vi}(s) = R_{vi} + jsL_{vi}$, R_{vi} , and L_{vi} keep constant at all frequencies. Consequently, merely one pair of variables is required to obtain the desired $Z_{vi}(s)$, and its impact can be easily implemented to various frequencies to realize accurate sharing of different power components, simplifying the controller design and saving computation resources.

Meanwhile, please note that generating X_i^* in Eq. (11) requires information exchange between different DGUs *via* communication links. Compared with droop control, the system reliability is degraded. To address this issue, the dependency on communication should be reduced.

In conventional methods, information exchange between DGUs is based on periodic communication. However, this is unnecessary in some conditions. When the power system has already reached a steady state or the power error is acceptable, no further impedance regulation is needed, and the only mission is remaining operation points of DGUs. Therefore, the event-triggered control (ETC) is employed. With this method, the corresponding controllers and communication links are triggered with preset triggering conditions [27]. As a result, the controller will be activated frequently when necessary and infrequently when the power error is reduced. That is, the controller and communication links are triggered in a nonperiodic way, and the communication resource is saved.

Another improvement solution is combining different methods. Based on the preceding illustration, it can be seen that accurate power sharing is achieved with frequency droops, but the voltage drop and frequency deviation are introduced. On the other hand, adaptive virtual impedance regulation ensures accurate power sharing without apparent voltage quality degradation, but communication is required for reference generation. To make the best of both methods, a decentralized control method is proposed to ensure power sharing in resistive microgrids in the work of Deng et al. [28], as presented in **Figure 6**, where the regulation process consists of two stages. In the first stage, power droop loops in Eq. (9) are implemented to generate the reactive power reference Q_i^* . Then, in the second stage, the virtual resistance is adaptively regulated based on the reactive power error. With this method, the feeder impedance mismatches are eliminated in a decentralized way, ensuring accurate power sharing at various frequencies without communication links. Therefore, system reliability is not degraded.

The above-mentioned power management strategies in islanded microgrids are comparatively analyzed in **Table 3**. In practical application, the suitable scheme can be determined based on control objectives.

6. Future trend of power management in renewable energy microgrids

In recent years, enormous cutting-edge techniques have emerged, and they can be exploited in the power management of renewable energy microgrids, to facilitate intelligent and digital development.

6.1 Integration of grid-forming converters

Grid-forming converters are power electronic inverters capable of forming voltage and frequency references in microgrids. They operate in voltage mode in grid-

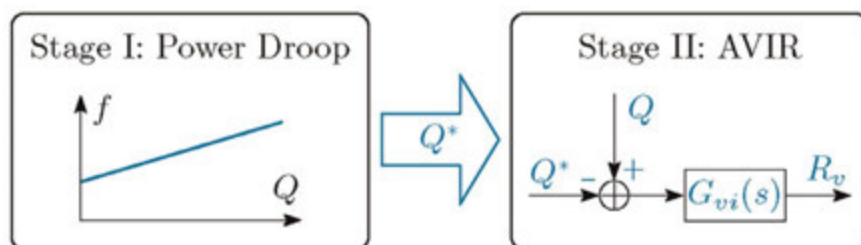


Figure 6.
 Two-stage decentralized power sharing.

Strategies	Advantages	Disadvantages
Power droop	Simple to implement	Voltage and frequency deviation
	Decentralized	Inaccurate power sharing
	Plug-and-play capability	Merely designed for certain power component
AVIR	Accurate power sharing	Relies on communication
	Excellent voltage quality	Poor scalability
Combined solutions	Accurate power sharing	Complicated implementation
	Decentralized	Requires accurate synchronization

Table 3.
Comparison between different power management strategies in islanded microgrids.

connected conditions, which enables seamless off-grid operation and enhances reliability, especially in weak grids [29]. Meanwhile, in this case, since both the utility grid and grid-tied inverters are operating as voltage sources, the application of grid-forming converters still faces some challenges. In grid-connected operation, the conventional overcurrent protection may fail due to limited fault current, which requires advanced protection techniques. Besides, in microgrids with multiple grid-forming converters, the interaction between different units may cause voltage and power oscillations, threatening system stability. When both grid-forming converters and grid-following converters are connected in the same microgrid, the coordination between them is another essential issue.

6.2 Multi-target cooperative power management

Existing power management strategies aim to realize various control targets, for example, equal/proportional power sharing to avoid overloading of some DGUs, economic dispatch to minimize operation cost [30], efficiency-oriented methods to reduce power loss [31], and reliability-oriented solutions to extend the lifespan [32]. However, the power distribution results with different strategies are conflicting. With a certain method, merely one of the above targets can be realized, which may not be the optimal solution. To address this issue, these control targets in various aspects must be cooperatively considered to form a flexible strategy, which adaptively adjusts the weights of these targets based on the specific application and requirements.

6.3 Digital twin and virtual power plants

A digital twin is a virtual replica of the power stage. It mirrors the behavior of renewable energy microgrids; it is constantly updated with real-time data *via* control systems, monitoring the instantaneous status of microgrids. Besides, a virtual power plant is an advanced energy management system that aggregates and coordinates DGUs into a unified energy entity.

Based on the combination of digital twins and virtual power plants, a powerful synergy can be built for the power management of renewable energy microgrids. Digital twins continuously update the performance and condition of renewable energy microgrids, and provide high-fidelity forecasts for operating conditions of elements and environmental conditions [33]. On this basis, virtual power plants dynamically

adjust control strategies to achieve optimal power management in the whole power system.

In the future, with increasing power system scale, the model accuracy and real-time synchronization between physical assets and digital models are still challenging. Besides, deploying the combination of digital twins and virtual power plants requires investment in cloud computing, modeling software, and human expertise, resulting in high initial costs and operating expenses.

6.4 AI-based predictive analytics and control algorithms

Artificial intelligence (AI) refers to computational systems that mimic human cognitive functions. It has drawn growing attention. In the power management of renewable energy microgrids, AI allows the power system to learn from historic operation data, forecast the output power of DGUs and the load demand profiles, and then realize optimal power distribution and load balance [34].

In real applications, the implementation of AI-based power management still faces challenges. AI-based forecast and control highly rely on model accuracy, but it is always degraded by noises and inaccurate measurements. Besides, for real-time execution, AI algorithms require heavy computational resources, which are quite expensive. Furthermore, nowadays, the AI models are black boxes, which lack interpretability and make it difficult for failure diagnosis and safe deployment.

7. Conclusions

The power management issues in renewable energy microgrids are illustrated. Firstly, the system structure and operation modes of microgrids are presented. Then, the power management issues in both grid-connected and islanded microgrids are discussed, and the corresponding solutions are also provided as follows.

7.1 Power management in grid-connected microgrids

- i. Power quality improvement to suppress the impact of unbalanced and harmonic load current on grid current, and it can be realized with PR control and repetitive control.
- ii. Inertia emulation to ease the impact of generation and load disturbances on grid frequency, it is achieved based on DC-side capacitors and DGUs.

7.2 Power management in islanded microgrids

Reducing the impact of mismatched feeder impedances and realizing equal or proportional power sharing between parallel DGUs.

Finally, the future trends of power management to facilitate intelligent and digital development of renewable energy microgrids are predicted.

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Advanced Multi-Agent Reinforcement Learning Strategy for Power Regulation in Standalone Microgrids

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Abstract

In this section, we outline a comprehensive and adaptive management technique for microgrids heavily reliant on inverters. This technique merges Multi-Agent Deep Reinforcement Learning (MADRL), leveraging the Twin Delayed Deep Deterministic Policy Gradient (TD3) method, alongside Virtual Synchronous Generator (VSG) mechanisms. Our solution facilitates equitable distribution of both active and reactive power across inverters in standalone microgrids, eliminating the dependence on inter-device communication or intricate system representations. Through a distributed framework for learning and implementation, every inverter operates as an autonomous entity that refines its decision-making rules through environmental engagements. Outcomes from computational tests reveal that the MADRL-VSG approach exceeds conventional VSG systems augmented with proportional-integral (PI) controllers in areas such as power allocation precision, frequency stability, and resilience to fluctuating demands.

Keywords: active power sharing, frequency control, inverter-based distributed generators, microgrid, voltage control, reactive power sharing, multi-agent deep reinforcement learning, twin delayed DDPG, virtual synchronous generator

1. Introduction

Inverter-based microgrids signify a major evolution in contemporary electrical networks, facilitating independent functionality by incorporating renewable energy resources (RESs) smoothly. These resources connect to the grid via power electronic interfaces (PEIs), necessitating specialized inverter control (IC) protocols to guarantee consistent and dependable performance. Typically, inverter control strategies fall into two main categories: grid-following (GFL) and grid-forming (GFM) [1, 2]. Of these, the Virtual Synchronous Generator (VSG) (a type of GFM) has attracted considerable interest due to its capability to replicate the inertia and damping properties of traditional synchronous machines, delivering superior reliability and

adaptability in connected as well as standalone configurations [3, 4]. Although VSG control stands out as a promising grid-forming solution, its standard application falls short in handling the complete array of control requirements in real-world microgrid settings.

Regarding active power sharing and frequency regulation, the VSG functions similarly to traditional droop mechanisms in equilibrium, allowing equitable energy input from interconnected inverters. First outlined in [5], this approach has evolved, including the adaptive decentralized controller introduced in [6], designed to boost both damping and power-sharing accuracy. That said, conventional VSG-based control experiences ongoing steady-state frequency deviations when facing load changes during islanded operation. To counteract this and reinstate system frequency, secondary control layers, often relying on proportional-integral (PI) controllers, are commonly added. Yet, when multiple inverters link to the point of common coupling (PCC) via mismatched impedance, it results in an offset in the load angle for each unit. This offset affects the P-F characteristics of the controller, disrupting the natural droop behavior and impairing the accuracy of active power sharing among IBDGs. Various model-based methods have been suggested to rectify this offset. For instance, the compensation-integral controller in [7] enhances frequency recovery via a centralized correction loop that calculates average output active power and disseminates it to every inverter. On the other hand, nonlinear control schemes like that in [8] have been investigated, utilizing feedback-based angle regulation to equalize power flow and restore frequency. Nonetheless, such techniques are challenging to tune or excessively reliant on exact system modeling.

Voltage regulation and reactive power sharing represent a second class of challenges in inverter-dominated microgrids. Due to the impedance mismatch of the feeders, the voltage drop across each feeder differs, causing a visible amount of RPSE [9]. To reduce RPSE, two broad strategies have been proposed in the literature: communication-based and decentralized approaches [10]. Communication-based methods, including the voltage drop estimation technique in [11] and the offline impedance tuning method in [12], attain improved sharing accuracy but demand complex architectures such as the inclusion of a virtual impedance loop, extensive tuning, and robust communication links. Other methods, such as those in [13, 14], rely heavily on detailed system modeling, which reduces their adaptability. Decentralized strategies, on the other hand, simplify implementation by relying on local measurements and droop tuning. However, these approaches often require trade-offs between RPSE reduction and voltage regulation performance. For instance, increasing the reactive power droop gain as seen in [15, 16] can reduce RPSE but at the cost of degraded voltage stability.

A persistent limitation across the aforementioned control strategies is their strong dependence on detailed mathematical modeling of the microgrid. This modeling process is usually tedious and typically involves linearizing a highly nonlinear system, which can introduce inaccuracies. Furthermore, with the ever-evolving nature of power system dynamics, control laws defined based on mathematical formulation would need to be updated to account for system changes. Moreover, limited access to key system parameters requires the use of estimation techniques, adding further complexity to controller design and reducing robustness under varying operating conditions. Given these considerations, the need for a model-free (data-driven) control strategy that can learn optimal behaviors from experience and maintain performance without explicit system models becomes increasingly compelling.

The progression of reinforcement learning (RL) has opened up innovative avenues for designing microgrid (MG) management systems, diminishing the need for intricate mathematical representations. Unlike conventional supervised and unsupervised learning techniques, which depend on pre-established data collections for training, RL allows entities to acquire ideal decision-making strategies via direct engagements with their surroundings. In these engagements, entities monitor situational conditions, choose responses, and refine subsequent actions according to incentive signals [17]. Earlier studies have investigated the use of Q-learning to dynamically adjust virtual inertia within VSGs [18]; nevertheless, its dependence on reference tables restricts its applicability in expansive, multi-faceted management environments [19]. To mitigate this, deep reinforcement learning (DRL) incorporates neural architectures, memory buffers for experiences, and auxiliary networks, rendering it appropriate for sophisticated MG management duties.

Contemporary investigations have illustrated the success of the Twin Delayed Deep Deterministic Policy Gradient (TD3) method in regulating grid-following as well as grid-forming inverters [20–23]. That said, much of this research has concentrated on isolated inverter setups and overlooks the synchronization issues prevalent in actual MGs featuring several IBDGs connected via uneven feeder resistances, which may adversely impact reactive power distribution.

To surmount this constraint, unified and multi-entity DRL (MADRL) structures have been examined. In our prior research [1, 24, 25], we presented a unified TD3 single-entity model as an initial demonstration. Within that configuration, one entity gathered situational data from every IBDG and generated the associated management directives. Although successful, this model necessitates a dependable data exchange network and struggles with expansion to broader setups. Additionally, in [24, 25], goals like reducing RPSE, APSE, ensuring voltage stability, and conducting frequency recovery were managed as independent functions, which added extra layers of intricacy.

To tackle these issues, MADRL offers a more extensible alternative. In MADRL, two key learning models are employed: centralized training with decentralized execution (CTDE) and completely independent training and execution (DTDE).

Under CTDE [26–28], entities undergo instruction with unified evaluators or collective overarching data to foster synchronized conduct. Yet, after implementation, each entity functions autonomously relying solely on nearby insights, enabling independent operation devoid of broad ongoing data sharing. Although this setup bolsters alignment in the learning phase, it might prove suboptimal when entities' responsibilities or setup arrangements vary.

Conversely, DTDE [29] employs an entirely independent methodology for both instruction and implementation. Every entity develops on its own, drawing from nearby and/or overarching situational and incentive details. For this study, DTDE is utilized to handle the varied management goals of the setup: one entity focuses on active power distribution and frequency recovery, whereas another concentrates on reactive power distribution and voltage stability.

The primary advancements outlined in this chapter are as follows:

1. The suggested management technique operates without any models, depending exclusively on situational readings and a thoughtfully crafted incentive mechanism to permit each IBDG within the MG to independently formulate its management strategy, thereby streamlining the creation of MG inverter regulators.

2. Entities receive instruction and are implemented via a DTDE structure, enabling them to manage unique management goals. As far as the authors are aware, this marks the initial use of MADRL to simultaneously address APSE, RPSE, voltage stability, and frequency recovery in microgrids reliant on inverters.

2. System description and problem statement

A typical VSG setup applied in grid-connected inverter scenarios is depicted in **Figure 1**. Initially, the 3ϕ inverters' injected current ($I_{o_{abc}}$) and terminal voltage ($V_{o_{abc}}$) are sensed and converted to the $dq0$ coordinate system. Next, the transformed current and voltage are used in computing the output active and reactive power P_{out} and Q_{out} .

A conventional VSG consists of two power control loops: Active Power Loop (APL) and Reactive Power Loop (RPL). The APL loop is governed by the synchronous generator swing equation, Eq. (1), hence enabling the VSG to provide virtual inertia.

$$P_{ref} - K_p(\omega - \omega_g) - D(\omega - \omega_g) - P_{out} = J\omega\dot{\omega} \quad (1)$$

From Eq. (1), P_{ref} , J , D , and K_p represent the active power set-point, virtual inertia, virtual damping factor, and active power droop coefficient, respectively. Meanwhile, ω and ω_g indicate the VSG's angular velocity and the standard grid angular velocity.

The inverter's power angle δ is governed by the frequency deviation between the virtual rotor and the reference grid:

$$\delta = \int (\omega - \omega_g) dt \quad (2)$$

For reactive power regulation, the Reactive Power Loop (RPL) employs a droop-based strategy coupled with integral feedback. The droop controller generates a reactive power reference Q_{ref} based on the deviation between nominal and actual voltage:

$$Q_{ref} = k_q(V_{nom} - v_d) + Q_{nom} \quad (3)$$

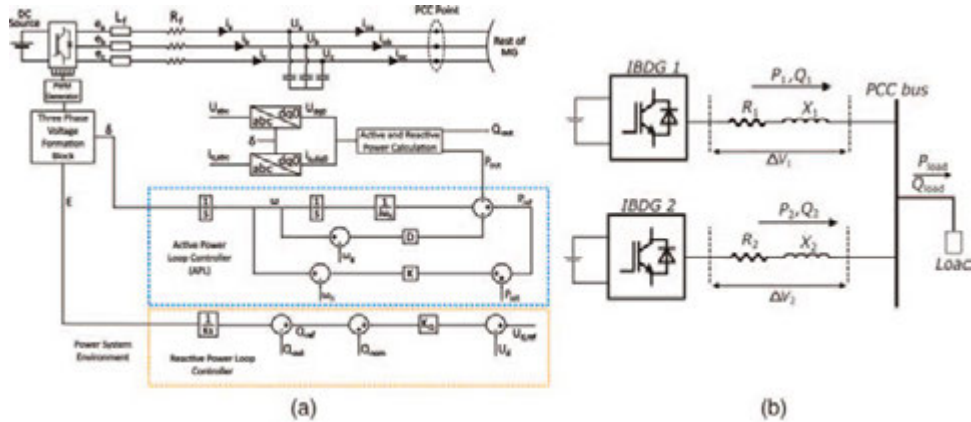


Figure 1.

(a) Architecture of a conventional VSG controlled inverter (b) Two inverter microgrid system [1, 24].

In this expression, V_{nom} and v_d represent the nominal and measured d -axis voltages, Q_{nom} is the nominal reactive power, and k_q is the voltage droop coefficient.

Eq. (4) is used to generate the inverter voltage magnitude E (signal),

$$E = \frac{1}{K_i} \int \Delta Q, dt \quad (4)$$

Where K_i is the integral gain and $\Delta Q = Q_{nom} - Q_{out}$ defines the reactive power tracking error.

Both control signals δ and E are then passed into a three phase voltage generator block and finally to the PWM generator to control the inverter switches.

This conventional control framework supports GFM operation but remains susceptible to performance issues such as steady-state frequency errors and poor reactive power sharing in the presence of mismatched feeder impedances. These limitations motivate the use of adaptive learning-based approaches explored in this work.

2.1 Active power sharing challenges in parallel VSG operation

In scenarios where VSGs function side by side, they apportion the overall demand based on their individual regulation settings. The power generated by each VSG depends on the aggregate demand as well as the manner in which energy is divided across the devices. This allocation is directed by the droop regulation traits of each VSG, which are essential for facilitating energy distribution and maintaining frequency stability in the setup. To examine how differing feeder impedance affect active power allocation, a setup with two inverters in an MG is evaluated. The behaviors of their regulation responses are reviewed in the subsequent manner [1].

$$\omega_1 = \omega_0 - K_{p_1}(P_1 - P_{nom}) \quad (5)$$

$$\omega_2 = \omega_0 - K_{p_2}(P_2 - P_{nom}) \quad (6)$$

At steady-state, $\omega_1 = \omega_2$, hence, we have that

$$K_{p_1}(P_1 - P_{nom}) = K_{p_2}(P_2 - P_{nom}) \quad (7)$$

For simplicity, set $P_{nom} = 0$:

$$K_{p_1}P_1 = K_{p_2}P_2 \quad (8)$$

Eq. (8) shows that the power sharing between two parallel VSG units is primarily governed by their respective droop control gains. However, a limitation of this approach is that the inherent nature of droop control introduces a post-transient frequency error. To mitigate this issue and improve long-term frequency accuracy, an integral controller is typically added to the APL. As a result, the original control relationships given in (5)–(6) are modified accordingly.

$$\omega_1 = \omega_0 - K_{p_1}(P_1 - P_{nom}) + K_{i_1} \int (\omega_1 - \omega_0) dt \quad (9)$$

$$\omega_2 = \omega_0 - K_{p_2}(P_2 - P_{nom}) + K_{i_2} \int (\omega_2 - \omega_0) dt \quad (10)$$

Recall from (2) $\delta = \int(\omega - \omega_0)dt$, therefore (9)–(10) can be rewritten as:

$$\omega_1 = \omega_0 - K_{p_1}(P_1 - P_{nom}) + K_{i_1}\delta_1 \quad (11)$$

$$\omega_2 = \omega_0 - K_{p_2}(P_2 - P_{nom}) + K_{i_2}\delta_2 \quad (12)$$

Therefore, at post-transient when $\omega_1 = \omega_2 = \omega_0$ and setting $P_{nom} = 0$ we get:

$$K_{p_1}P_1 + K_{i_1}\delta_1 = K_{p_2}P_2 + K_{i_2}\delta_2 \quad (13)$$

Eq. (13) reveals that adding the δ_i components from integrative regulation alters the strict adherence to power allocation in (8). In MGs where feeder resistances are uniform across IBDGs, this adjustment has little effect, given the uniform error adjustments. But in MGs featuring varied feeder resistances, the dissimilarities cause inconsistent phase adjustments, leading to disparate integrative fixes among IBDGs. Such differences upset the desired equitable power allocation, resulting in shifts away from the optimal spread defined by droop traits.

2.2 Reactive power sharing challenges in parallel VSG operation

To examine the root cause of poor reactive power sharing, consider the two-inverter MG setup shown in **Figure 1b**. Here, IBDG₁ and IBDG₂ are connected to a common load via distinct feeder lines with impedances (R_1, X_1) and (R_2, X_2) , respectively. The voltage drops across these feeders can be approximated as follows [1, 30]:

$$\Delta V_1 = \frac{R_1P_1 + X_1Q_1}{V_o} \quad (14)$$

$$\Delta V_2 = \frac{R_2P_2 + X_2Q_2}{V_o} \quad (15)$$

The line impedance differences are defined by:

$$\Delta R = R_1 - R_2 \quad (16)$$

$$\Delta X = X_1 - X_2 \quad (17)$$

Rewriting R_1 and X_1 in terms of R_2 and X_2 (taken as reference values):

$$R_1 = \Delta R + R \quad (18)$$

$$X_1 = \Delta X + X \quad (19)$$

Substituting into (21) yields the following expression [32]:

$$\Delta V_1 = \frac{(\Delta X + X)Q_1 + (\Delta R + R)P_1}{V_o} \quad (20)$$

Which simplifies to:

$$\Delta V_1 \approx \frac{\Delta XQ_1 + \Delta RP_1}{V_o} + \frac{XQ_1 + RP_1}{V_o} = \delta V_1 + \Delta \bar{V}_1 \quad (21)$$

Assuming V_{pcc} is the common reference voltage, the inverter output voltages become:

$$\begin{aligned} E_1 &= V_{pcc} + \Delta V_1 + \delta V_1 \\ E_2 &= V_{pcc} + \Delta V_2 \end{aligned} \quad (22)$$

Here, $\Delta \bar{V}_1$ represents the nominal drop based on reference impedance values, while δV_1 captures the mismatch error caused by impedance asymmetry between feeders. This error results in uneven voltage drops, leading to inaccurate reactive power sharing across the IBDGs [14, 31, 32].

Achieving ideal reactive power sharing would require $\delta V_1 = 0$, implying $R_1 = R_2$ and $X_1 = X_2$, which is rarely achievable in practice. Moreover, even with impedance matching, unequal IBDG capacities can still introduce imbalance, as higher-capacity units naturally supply more power and experience larger voltage drops. This further degrades reactive power sharing accuracy, emphasizing the need for advanced control strategies.

To address the challenges discussed in Section 2.1 and 2.2, various methods have been explored by researchers. Majorly, these methods rely heavily on accurate mathematical modeling to design sophisticated controllers like model predictive control [33–35] which often relies on linearizing a highly non-linear system leading to over-approximation or loss of key system dynamics. In addition, since not all state variables are easily available, estimation techniques are often deployed to estimate these hidden states, further complicating the control design. Lastly, and more importantly, due to the ever evolving nature of power system networks, most model-based methods require extensive revisions of the mathematical model to have them operate efficiently [36]. In our earlier work [24, 25], we demonstrated the effectiveness of a single-agent DRL approach for achieving either voltage regulation with reduced RPSE or frequency restoration with reduced APSE. However, addressing these objectives in isolation is not sufficient for ensuring overall system performance. A more comprehensive solution must simultaneously manage all four control objectives to enable resilient, stable, and scalable microgrid operation. To address this concern, this work adopts a MADRL strategy aimed at learning fully decentralized control policies capable of simultaneously addressing all four control objectives. Moreover, the proposed approach is entirely model-free, eliminating the need for accurate mathematical modeling and offering greater flexibility and adaptability to system changes.

2.3 Training multi-agents

Within Multi-Agent Deep Reinforcement Learning (MADRL), entities may exhibit collaborative or adversarial patterns based on the instructional methodology. Common frameworks include Centralized Training with Decentralized Execution (CTDE) and Decentralized Training with Decentralized Execution (DTDE) [1, 26, 37].

Under CTDE, the evaluator for every entity forms part of a unified system that assesses the combined action-value function $Q(s, a_1, a_2, \dots, a_N)$, with s denoting the overarching system condition and a_i indicating the choice made by entity i . The strategy variables θ_i for entity i undergo refinement via:

$$\nabla_{\theta_i} J(\pi_i) = \mathbb{E}_{\tau} [\nabla_{\theta_i} \log \pi_i(a_i | s_i; \theta_i) Q(s, a_1, \dots, a_N)] \quad (23)$$

Post-training, the acquired strategy $\pi_i(a_i | s_i; \theta_i)$ facilitates independent implementation, allowing each entity to decide solely from its nearby insight s_i . This blended

methodology permits entities to leverage overarching alignment in the instructional phase while functioning autonomously during application [38]. That said, entities instructed and applied this way may encounter difficulties amid inconsistencies in the setup or management goals [1, 26]. In opposition, DTDE reduces data sharing across both instructional and application stages. Each entity refines its strategy on its own, relying on nearby condition s_i and a restricted action-value function $Q_i(s_i, a_i)$ expressed as:

$$Q_i(s_i, a_i) = \mathbb{E}_{\tau_i} \left[\sum_{t=0}^T \gamma^t r_t(s_i, a_i) \right] \quad (24)$$

in which $r_t(s_i, a_i)$ signifies the prompt incentive, $\gamma \in [0, 1]$ acts as the reduction coefficient, and τ_i represents the path of entity i . The adjustment for the strategy evolves into:

$$\nabla_{\theta_i} J(\pi_i) = \mathbb{E}_{\tau_i} [\nabla_{\theta_i} \log \pi_i(a_i | s_i; \theta_i) Q_i(s_i, a_i)] \quad (25)$$

For this investigation, DTDE is employed to support entirely independent strategy acquisition. This method aligns effectively with the scenario, as each entity handles a distinct management aim; one oversees reducing the APSE and reinstating frequency, whereas the second concentrates on lessening the RPSE and stabilizing voltage. Through autonomous refinement from nearby data, entities gain durability against data lags or disruptions, boosting extensibility and durability in microgrid setups.

2.4 Basics of TD3 algorithm

In this study, TD3 (Twin Delayed DDPG) serves as a reinforcement learning method for ongoing control tasks. The TD3 resolves DDPG's issue of critic overestimation that results in poor strategies and shaky training. Main improvements feature postponed actor refinements, dual critics, and target policy smoothing as regularization [39].

2.4.1 Network architecture

According to **Figure 2**, the TD3 method relies on an actor-critic framework involving six neural structures: one actor network π_ϕ , a pair of critic networks Q_{θ_1} and Q_{θ_2} , plus their matching target versions $\pi_{\phi'}$, $Q_{\theta'_1}$, and $Q_{\theta'_2}$. The actor handles the selection of ideal responses from given conditions, whereas the critics gauge the anticipated yield (Q-value) for state-response combinations. Target networks serve as lagged counterparts to the primary ones, promoting steadier instruction by offering reliable benchmarks for time-based variance adjustments.

Training begins with arbitrary parameter setup across all networks. A memory pool for experiences is established to hold shift sets (s_t, a_t, r_t, s_{t+1}) gathered from entity-surroundings exchanges. Drawing arbitrary small groups from this pool disrupts sequential links in the information, boosts instructional productivity, and aids superior alignment.

The actor learns to mimic the best strategy $\pi(a_t | s_t)$, linking observed scenarios to choices that enhance extended anticipated gains. Concurrently, the dual critics appraise response effectiveness via $Q_i(s_t, a_t | \theta_i)$ estimates. Employing twins mitigates

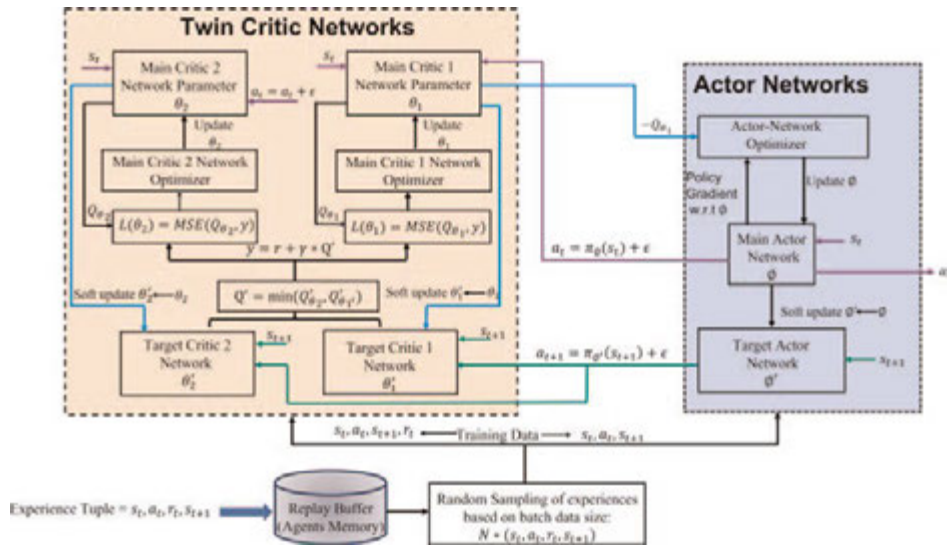


Figure 2.
 Detailed TD3 agent structure [21].

the upward skew typical in solo-critic designs, yielding more trustworthy instructional cues.

Each critic network employs a two-path setup: one pathway processes state inputs, while the other handles action inputs. These are managed separately at first, then merged and passed into joint hidden layers for further analysis. This design helps the network better understand and learn from the blended state-action information, enhancing its skill in assessing actions across different situations.

By combining delayed policy updates, clipped double Q-learning, and target networks, TD3 offers improved learning stability and policy performance in continuous action spaces, making it a suitable candidate for complex control problems [25, 39].

For this study, the inner layers in critic and actor networks, including targets, employ the ReLU activator outlined in Eq. (26).

$$\text{ReLU}(x) = \max(0, x) \quad (26)$$

For the actor network out, the TanH given in Eq. (27) activation is used

$$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (27)$$

2.4.2 Agent-environment interaction

As previously discussed, DRL agents learn control policies by engaging with their environment, observing states, selecting suitable actions, and earning rewards. Over-time, the goal of the agent is to maximize the cumulative rewards it receives throughout its interaction with the environment. In this research, a multi-agent DRL system is applied, with each agent functioning independently, using just its local state details (s_t) to produce relevant actions (a_t).

Agents run through a fixed count of training steps (T_s) in every episode. Training starts with agents having zero environment knowledge, as their network parameters

begin randomized. For better exploration, Gaussian noise gets added to the actor network’s action outputs, fading gradually to prioritize exploitation over time.

$$a(t) = \pi_\phi(s_t) + \zeta \epsilon \quad (28)$$

At each time step, the agent executes action a_t while in state s_t , moves to the following state s_{t+1} , and gets a reward r_t . This exchange creates a transition set (s_t, a_t, r_t, s_{t+1}) , saved in a limited-size memory pool B . Small random groups are pulled from this pool to refine the agent’s networks. When fresh data enters, outdated entries are removed, keeping emphasis on current engagements and promoting reliable learning and alignment. Further details regarding the training process of the agents can be found in [17, 21, 39].

2.4.3 Training the networks

As noted earlier, the DDPG algorithm suffers from overestimation bias and sensitivity to hyperparameter tuning. TD3 addresses these by introducing twin critic networks (and their targets) for more stable value estimates.

During training, the two critics independently evaluate the current state s_t and action a_t to produce Q-values $Q_{\theta_i}(s_t, a_t)$. The target critics assess the next state s_{t+1} and action a_{t+1} for future Q-values $Q'_{\theta_i}(s_{t+1}, a_{t+1})$.

TD3 adds two key improvements:

- i. Target policy smoothing: Deterministic policies can overestimate Q-values due to action sensitivity [39]. TD3 adds noise to the target actor’s next action $\tilde{a}_{t+1}$, then computes target Q-values $Q'_{\theta_i}(s_{t+1}, \tilde{a}_{t+1})$. To avoid bias, it uses the minimum of the two target critics:

$$y = r + \gamma \min_{i=1,2} \left(Q_{\theta'_i}(s', \tilde{a}) \right) \quad (29)$$

Here, r is the immediate reward, and γ (0 to 1) balances short vs. long-term rewards low γ favors quick gains, high γ emphasizes future returns.

Critics update via mean squared error loss:

$$Loss_{\theta_i} = MSE(y - Q_{\theta_i}(s, a)) \quad (30)$$

Gradients of this loss adjust critic weights using an optimizer like Adam.

- ii. Actor network update: Updates are delayed (every d steps) to reduce variance. The actor loss gradient is:

$$\nabla_\phi J(\phi) = N^{-1} \sum \nabla_a Q_{\theta_1}(s, a) \Big|_{a=\pi_\phi(s)} \nabla_\phi \pi_\phi(s) \quad (31)$$

This optimizes parameters ϕ to maximize Q-values from the first critic. Gradients update the actor.

Target networks update softly:

$$\theta_i = \tau \theta_i + (1 - \tau) \theta'_i \quad (32)$$

$$\phi_i = \tau\phi_i + (1 - \tau)\phi'_i \quad (33)$$

The parameter τ controls the update speed for gradual tracking.

2.5 State and action

As established, each DRL agent interacts with the environment by observing states, selecting actions, and receiving feedback in the form of rewards. In this study, two distinct agents are designed; one for active power sharing and frequency regulation, and another for reactive power sharing and voltage regulation.

For the active power agent, the state and action vectors are defined as:

$$s_t = [F_i, F_j, P_{out_i}, P_{out_j}] \quad (34)$$

$$a_t = [P_{ref_i}, P_{ref_j}] \quad (35)$$

where F_i and F_j are the frequencies, and P_{out_i} and P_{out_j} are the active power outputs of IBDG_i and IBDG_j.

For the reactive power agent, the state and action vectors are given by:

$$s_t = [v_{d_i}, v_{d_j}, Q_{out_i}, Q_{out_j}] \quad (36)$$

$$a_t = [Q_{ref_i}, Q_{ref_j}] \quad (37)$$

where v_{d_i} and v_{d_j} are the d -axis voltages, and Q_{out_i} and Q_{out_j} are the reactive power outputs of the two IBDGs.

At each time step, an action a_t is computed based on the current state s_t and applied to the environment. The system then transitions to a new state s_{t+1} and yields a reward r_t . This experience, (s_t, a_t, r_t, s_{t+1}) , is stored in a finite replay buffer B . To update the networks, random mini-batches are sampled from B , helping to break correlations in training data. As the buffer fills, older experiences are discarded, ensuring that learning remains focused on recent, diverse transitions, thereby improving agents' convergence towards the optimal policy.

2.6 Reward definitions

2.6.1 Active power sharing and frequency regulation reward definition

The following set of reward descriptions are crafted to ensure the agent finds an optimal strategy that regulates the frequency back to post-disturbance setpoint, while ensuring minimized APSE.

2.6.1.1 Frequency regulation

Given that the active power loop of the conventional VSG controller behaves similarly to the droop control, an approach known to result in steady-state frequency deviations, the corresponding reward component is crafted to address and reduce this frequency error during learning.

$$\text{Reward}_F = -k_1|e_f| - k_2 \int |e_f| dt \quad (38)$$

In Eq. (38), $|e_f|$ represents the absolute frequency deviation, given by $|F_i - F_{ref}|$. Here, F_i is the observed frequency for the i th IBDG, and F_{ref} is the target frequency. Thus, $|e_f|$ captures the difference between the current and ideal frequency at that instant.

The incentive setup features two penalty terms, k_1 and k_2 , that influence the agent's instructional patterns. k_1 applies a penalty when the deviation surpasses a set limit of 0.001, deterring significant drifts. Meanwhile, k_2 adds a steady negative penalty to motivate swift return of the frequency to its standard level.

2.6.1.2 Minimize APS error

To mitigate this trade-off between frequency restoration and accurate power sharing, a dedicated reward function is designed to promote an accurate active power distribution while maintaining frequency stability.

$$\text{Reward}_P = -k_3|e_p| - k_4 \int (|e_p|) dt \quad (39)$$

Where $e_p = |P_{exp} - P_{out}|$ in Eq. (39), representing the APSE for each IBDG. In this expression, P_{exp} is the expected power contribution, while P_{out} is the actual measured output power. Two penalty weights, k_3 and k_4 , are used to scale the reward based on the deviation of P_{out} from P_{exp} . These penalties are designed to discourage large deviations, thus guiding each IBDG to align its output with its expected share of active power. For clarity, P_{exp} is given as:

$$P_{exp} = P_{pcc} \cdot \frac{S_{rating}^{IBDG_i}}{S_{MGcapacity}} \quad (40)$$

Where P_{pcc} denotes the measured point-of-common-coupling power demand, $S_{rating}^{IBDG_i}$ is the capacity rating of the i^{th} IBDG, and $S_{MGcapacity}$ represents the combined capacity of all generation units in the system. The expected power output P_{exp} for each IBDG is proportional to its rating relative to the total microgrid capacity. The penalty coefficient k_3 assigns a large negative reward if the APSE e_p exceeds a predefined threshold, and a smaller penalty otherwise. This structure encourages the agent to minimize deviations from the expected power contribution. Additionally, the term k_4 is a constant penalty that consistently reinforces the reduction of active power dispatch errors throughout the learning process.

2.6.1.3 APS ratio constraint

To ensure fair active power contributions from IBDGs in proportion to their capacity ratings, the reward Eq. (41) is designed:

$$\text{Reward}_{IBDG_Ratio} = -k_5 \cdot \text{IBDG}_{ratio} \quad (41)$$

where the ratio term is defined as:

$$IBDG_{ratio} = \frac{P_{IBDG_1}}{\sum_{j=2}^n P_{IBDG_j}} \quad (42)$$

Here, k_5 is a penalty coefficient. When the contribution of an IBDG deviates significantly from the expected range, k_5 applies a large negative reward; otherwise, a smaller penalty is given to encourage proportional power sharing.

Combining all three objectives, THE cumulative reward for the agent at time step t is:

$$Reward_{agent1_total,t} = Reward_{F_t} + Reward_{P_t} + Reward_{IBDG_Ratio} \quad (43)$$

The agent's goal is to maximize this total reward by learning control actions that balance all three objectives effectively.

2.6.2 Reactive power sharing and voltage regulation

2.6.2.1 Voltage regulation

In autonomous mode, GFM inverters are primarily responsible for maintaining voltage and frequency stability. As such, the TD3 agent must effectively regulate the voltage at each IBDG to preserve the overall stability of the MG. To meet operational standards, the voltage is expected to remain within a tolerance band of ± 0.05 pu. To reflect this objective, the voltage regulation reward is formulated as follows:

$$Reward_v = -k_1|e_v| \quad (44)$$

From the above Eq. (44), the voltage error is defined as $|e_v| = |V_i - V_n|$, where V_i denotes the output voltage of the i^{th} IBDG and V_n is the nominal voltage level, both in per-unit. A penalty coefficient k_1 is employed to influence the agent's learning based on the magnitude of the voltage error. When $|e_v|$ exceeds the specified threshold, a larger penalty is applied by increasing k_1 , discouraging deviations. On the other hand, smaller voltage errors incur a minor penalty, reinforcing acceptable behavior.

2.6.2.2 Minimizing RPS error

Similarly, conventional droop control methods often result in poor reactive power sharing (RPS) when line impedance mismatches exist between IBDGs. Hence, the reactive power measured at the PCC is integrated into the agent's reward structure to promote balanced reactive power contribution among IBDGs.

$$Reward_Q = -k_2|e_q| - k_3 \int (|e_q|) \quad (45)$$

In (45), the coefficients k_2 and k_3 serve as penalty weights related to RPSE, while k_4 penalizes deviations in the proportional contribution of i^{th} IBDG relative to its capacity. The RPSE term, denoted as $|e_q|$, captures the deviation between the expected and actual reactive power outputs and is defined as $e_q = |Q_{share} - Q_{out}^{IBDG_1}|$. The expected reactive power contribution Q_{share} is given by:

$$Q_{\text{share}} = Q_{\text{pcc}} \cdot \frac{S_{\text{rating}}^{\text{IBDG}_i}}{S_{\text{MGcapacity}}} \quad (46)$$

Here, Q_{pcc} is the total reactive power demand at the PCC, $S_{\text{rating}}^{\text{IBDG}_i}$ is the rating of the i^{th} IBDG, and $S_{\text{MGcapacity}}$ is the combined capacity of all IBDGs in the microgrid. When e_q exceeds a defined error threshold, k_2 increases significantly to apply a strong penalty; otherwise, it applies a smaller penalty. The constant term k_3 encourages the agent to consistently reduce RPSE over time.

2.6.2.3 RPS ratio constraint

To ensure each IBDGs contribute fairly to the reactive load demand, the following reward is defined:

$$\text{Reward}_{\text{IBDGRatio}} = -k_4 \text{IBDG}_{\text{ratio}} \quad (47)$$

where the term $\text{IBDG}_{\text{ratio}}$ is expressed as:

$$\text{IBDG}_{\text{ratio}} = \frac{Q_{\text{IBDG}_{i=1}}}{\sum_{j=2}^n Q_{\text{IBDG}}} \quad (48)$$

The term k_4 serves as the penalty associated with $\text{IBDG}_{\text{ratio}}$. If the reactive power contribution of any IBDG falls outside the expected contribution boundary, k_4 is assigned a large negative reward. Otherwise, when the contribution remains within the desired limits, k_4 is set to a smaller negative reward.

Based on (44)–(47), the cumulative reward the agents receives in each iteration (t) is expressed as:

$$\text{Reward}_{\text{agent2_total}} = \text{Reward}_{v_t} + \text{Reward}_{Q_t} + \text{Reward}_{\text{IBDG_Ratio}} \quad (49)$$

3. Result and discussion

Based on the reward structures defined in Eqs. (43) and (49), the two agents are trained to perform distinct control tasks: Agent 1 is optimized for minimizing APSE and achieving frequency restoration, while Agent 2 is trained to minimize RPSE and maintain voltage regulation. The DTDE framework is adopted to accommodate the agents' specialized objectives. As illustrated in **Figure 3**, both agents are trained over 1500 episodes, requiring approximately 6 hours on a 13th Gen Intel Core i9 2.60GHz ASUS laptop.

To evaluate the efficacy of the proposed control strategy, the trained agents are deployed in a two-inverter microgrid system, as illustrated in **Figure 4**, with both IBDGs equally rated. Their performance is benchmarked against two baseline approaches: (i) conventional VSG control without frequency restoration, and (ii) an enhanced VSG strategy incorporating frequency restoration. **Tables 1** and **2** summarizes the key parameters of the microgrid and the MADRL agents. Additionally, to ensure continuous and stable operation, classical VSG droop control is retained as a redundancy mechanism in the event of agent-microgrid communication loss.

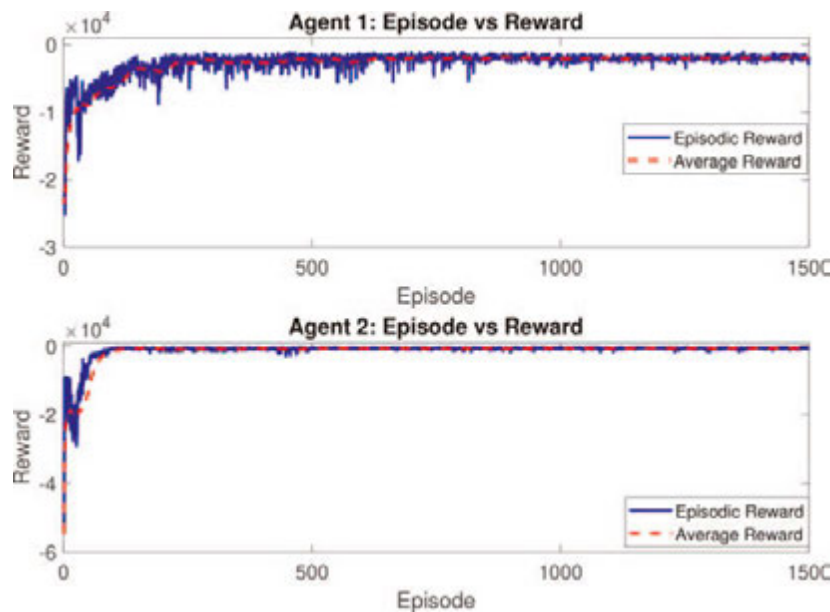


Figure 3.
Agents training progress.

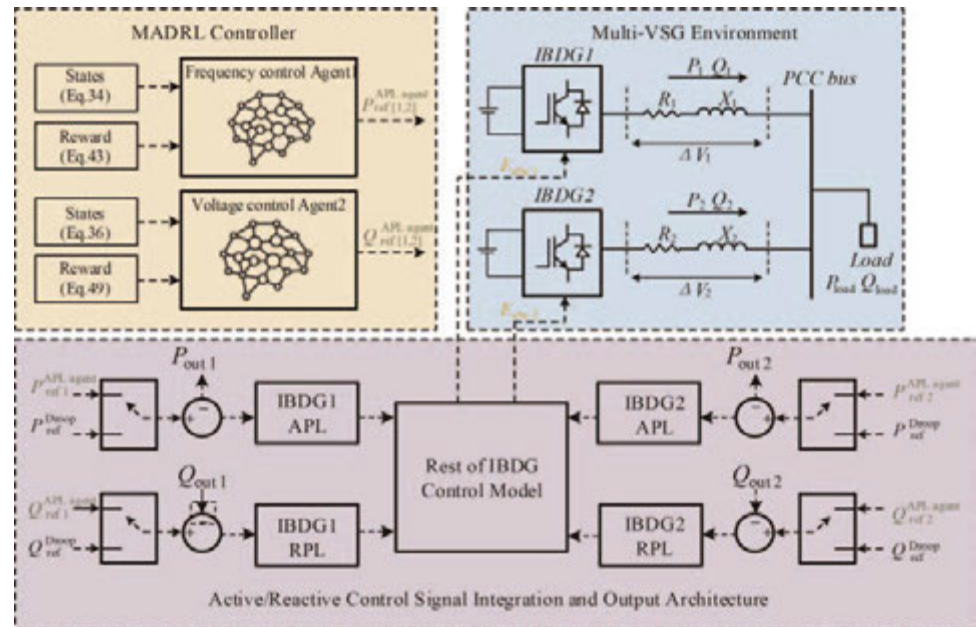


Figure 4.
Integrated MADRL agents for two inverter network.

3.1 Test 1: Load perturbations

As previously mentioned, Agent 1 is tasked with controlling both IBDGs to minimize APSE and restore system frequency, while Agent 2 is trained to achieve low

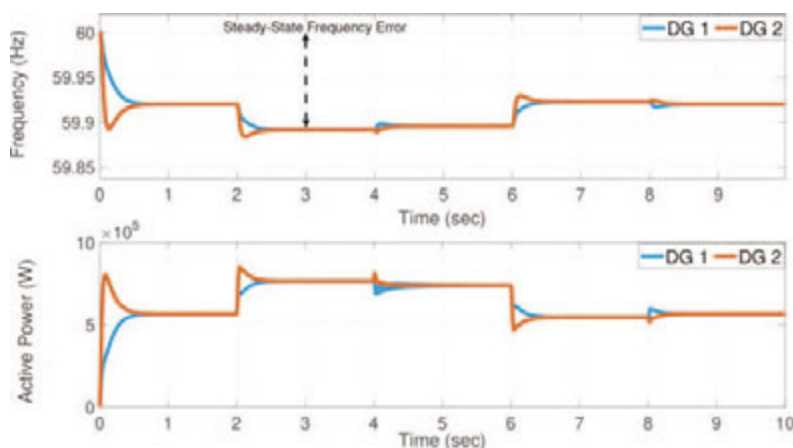
Parameter	Value
S_{MG} (Microgrid capacity)	6000 kVA
V_{nom} (Nominal voltage)	13.8 kV
R_{filter}	1.9 m Ω
L_{filter}	0.05 mH
Z_{line_1}	$R_{line} = 6 \text{ m}\Omega, L_{line} = 40.35 \text{ mH}$
Z_{line_2}	$R_{line} = 0.1 \Omega, L_{line} = 40 \mu\text{H}$
F_{norm} (Nominal frequency)	60 Hz
Error Tolerance	5%
J (Virtual inertia)	3.5×10^{-5}
D (Virtual damping)	0.45

Table 1.
Microgrid (MG) network parameters.

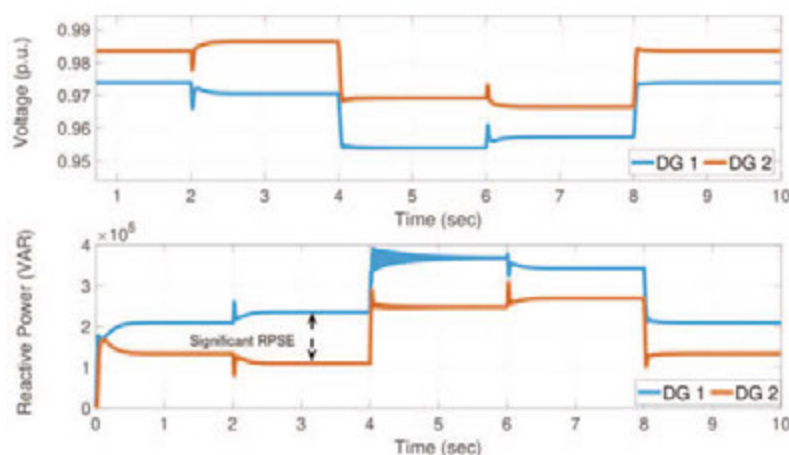
Parameter	Value	Notes
Actor Learning Rate	1×10^{-4}	Optimizer: Adam
Critic Learning Rate	2×10^{-4}	Optimizer: Adam
Target Network Update Rate	5×10^{-3}	τ (soft update factor)
Replay Buffer Size	2×10^6	Experiences stored
Batch Size	64	Mini-batch training
Discount Factor (γ)	0.99	Long-term reward weighting
Exploration Noise (σ)	0.1 (decaying)	Gaussian noise + ϵ -greedy
Actor Network Architecture	[4, 128, 64, 2]	Hidden: ReLU, Output: Tanh
Critic Network Architecture	[2, 64], [2, 64], [64, 32, 1]	Hidden layers use ReLU
Penalty Weights (Large)	[5000, 5000, 500]	Frequency/voltage scaling
Penalty Weights (Small)	[0.05, 0.05, 0.05]	Reactive power scaling
Training Episodes	1500	$\approx$ 6 hours on Intel i9 CPU
Software/Hardware	MATLAB/SIMULINK 2024b	ASUS Laptop (i9, 2.60 GHz)

Table 2.
 TD_3 agent and DRL training parameters.

RPSE and maintain voltage regulation. To evaluate the dynamic performance of each control strategy, the PQ load within the microgrid is varied at multiple time intervals. The response of the conventional VSG control is presented in **Figure 5**. As observed, the system exhibits a notable steady-state frequency error, indicating the absence of a frequency restoration mechanism. In contrast, the voltage at each IBDG remains well-regulated within the acceptable margin of $1 \pm 0.5\text{pu}$. Despite the presence of line impedance mismatch, active power sharing remains accurate, which aligns with the theoretical expectations discussed in Section. 2.1. However, due to the unequal voltage



(a) Active power sharing performance under load sweep with NormControl.



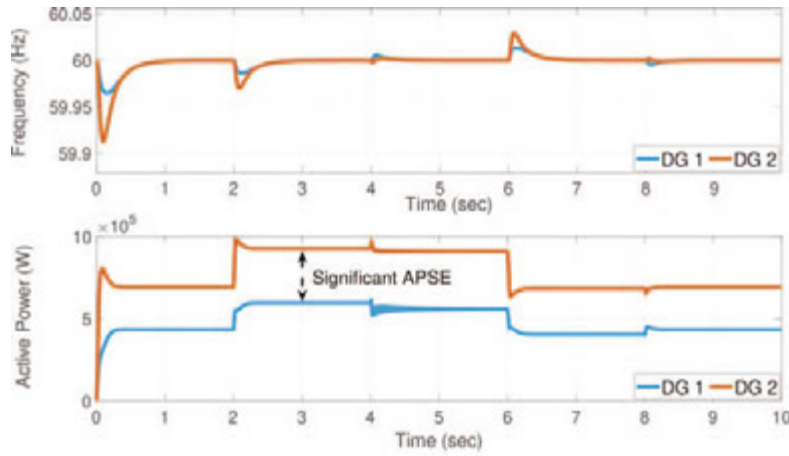
(b) Voltage and reactive power sharing under load sweep with NormControl.

Figure 5.
 Load sweep test results using the conventional VSG control strategy.

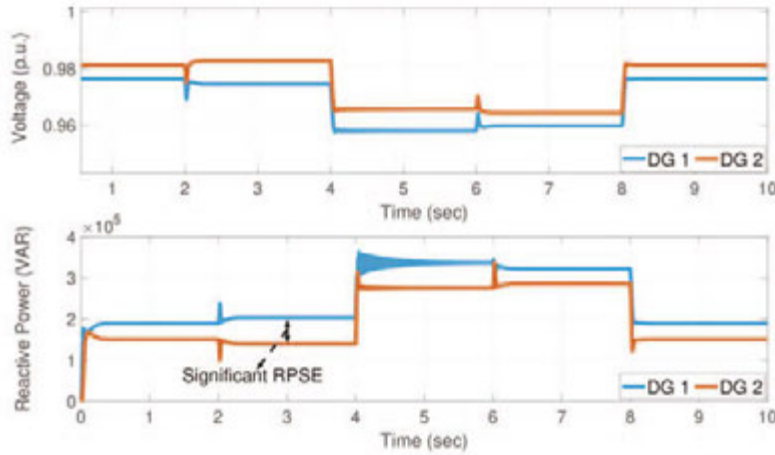
drops introduced by the impedance disparity across feeders, the system experiences a significant RPSE.

Figure 6 illustrates the response of VSG with the PI frequency restoration control. As shown, the frequency of both IBDGs remains tightly regulated around the nominal value throughout the load sweep. However, the mismatch in feeder impedance leads to a noticeable APSE, owing primarily to the integrator controller which introduces an offset in the load angle of each IBDG post-transient. This adversely affects active power sharing, aligning with the theoretical analysis presented in Section. 2.2. Furthermore, although voltage regulation is maintained, a significant RPSE persists between the two IBDGs, highlighting poor reactive power coordination.

The performance of the proposed MADRL-TD3-based VSG control strategy is illustrated in **Figure 7**. As shown, throughout the load sweep the frequency of the IBDGs remains tightly regulated at 60 Hz, and the voltage deviations caused by load variations are confined within the bounds specified by the reward function. In



(a) Active power sharing performance under load sweep with PI-Control.

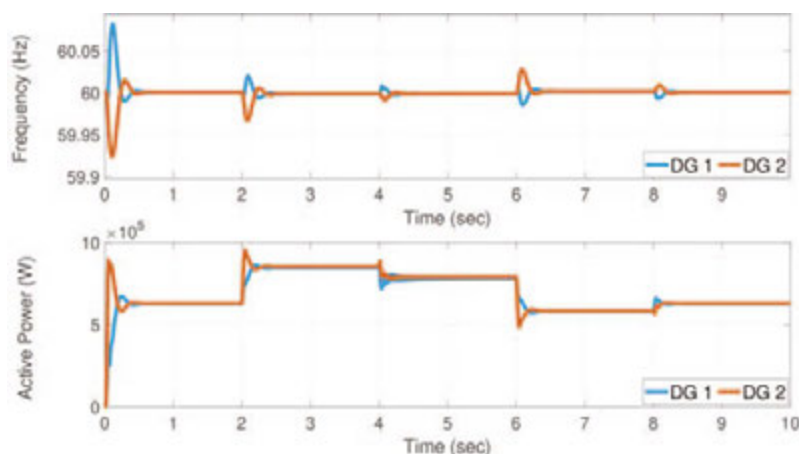


(b) Voltage and reactive power sharing under load sweep with PI-Control.

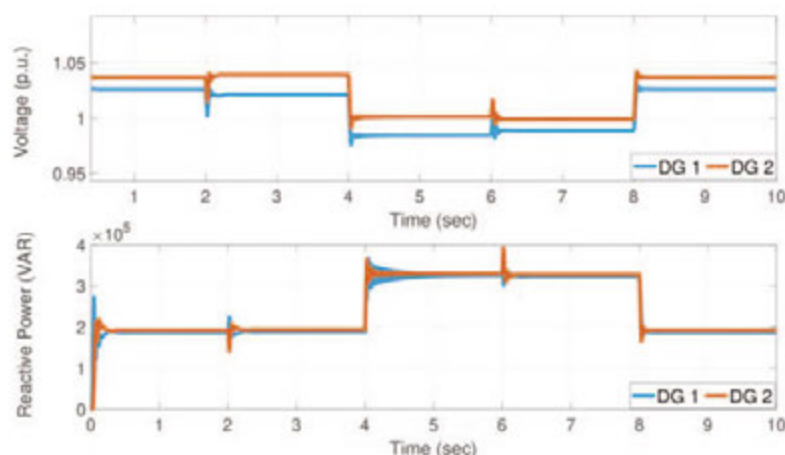
Figure 6.
Load sweep test results using the PI-enhanced VSG.

addition to maintaining frequency and voltage regulation, the MADRL-VSG also achieves accurate active and reactive power sharing. These results highlight both the effectiveness of the proposed approach in meeting the control objectives.

Table 3 shows a qualitative side-by-side comparison of the controllers under the same load-sweep. In summary, the Conventional VSG (no PI) maintains voltage and preserves droop-based active-power sharing but exhibits a steady-state frequency error and large RPSE under feeder-impedance mismatch; the PI-VSG removes the frequency error yet introduces APSE due to the integrator-induced phase offset while RPSE remains high; the proposed MADRL controller simultaneously holds frequency at 60 Hz, keeps voltage within bounds, and achieves low APSE/RPSE. For completeness, the table also lists a Single-Agent DRL row as expected behavior (not simulated here): such a centralized policy would likely regulate frequency but introduce trade-offs in sharing accuracy and scalability relative to the decentralized MADRL approach.



(a) Active power sharing performance under load sweep with MADRL-Control.



(b) Voltage and reactive power sharing under load sweep with MADRL-Control.

Figure 7.
 Load sweep test results using the MADRL-based control strategy.

3.2 Test 2: Redundancy test

Despite the demonstrated effectiveness of the MADRL strategy in meeting the fourfold control objectives, it is crucial to evaluate its resilience under potential operational disturbances. To this end, a contingency test is conducted wherein the MADRL agents are deliberately disconnected and subsequently reconnected to assess the system's fault tolerance and reconnection behavior.

In **Figure 8a**, at $t = 1$ s, IBDG 1 loses access to control signals from Agent 1, while IBDG 2 remains under MADRL control. This results in a deviation of the system frequency from the nominal 60 Hz. To maintain microgrid stability during this event, the control framework seamlessly transitions from MADRL to conventional VSG control. However, this transition leads to a noticeable increase in APSE, reflecting the performance trade-off.

Controller	Frequency regulation	Active power sharing (APSE)	Reactive power sharing (RPSE)	Voltage regulation
Conventional VSG (no PI)	Steady-state error present	Accurate (droop-based)	Significant RPSE under impedance mismatch	Maintained within 1 ± 0.05 pu band
PI-VSG	Tight around nominal	Noticeable APSE due to integrator-induced δ offset	Significant RPSE persists	Maintained
MADRL (this work)	Tight at 60 Hz	Accurate sharing (low APSE)	Accurate sharing (low RPSE)	Deviations bounded by reward design
Single-Agent DRL VSG (expected)	Expected tight regulation (if trained)	Expected trade-offs when bundling all control tasks into a single policy	Expected imperfect coordination vs. MADRL; scalability issues likely	Expected maintained

Note: The single-agent DRL row reports expected behavior only; it was not simulated in this chapter. More information on Single agent application can be found in our earlier publications [24, 25].

Table 3.
Performance comparison across controllers under load-sweep tests.

Similarly, in **Figure 8b**, at $t = 2$ s, the reactive power loop of IBDG 1 experiences a disruption in control signals from Agent 2. Consequently, the system reverts to a Q-V droop strategy to preserve operational continuity. While the voltage profile remains relatively stable, a substantial increase in RPSE is observed following the control switch.

Subsequent reconnection of MADRL agents is achieved at $t = 5$ s in **Figure 8a** and $t = 6$ s in **Figure 8b**. Upon restoration, both frequency and voltage regulation are promptly recovered, as evidenced by the marked reduction in APSE and RPSE.

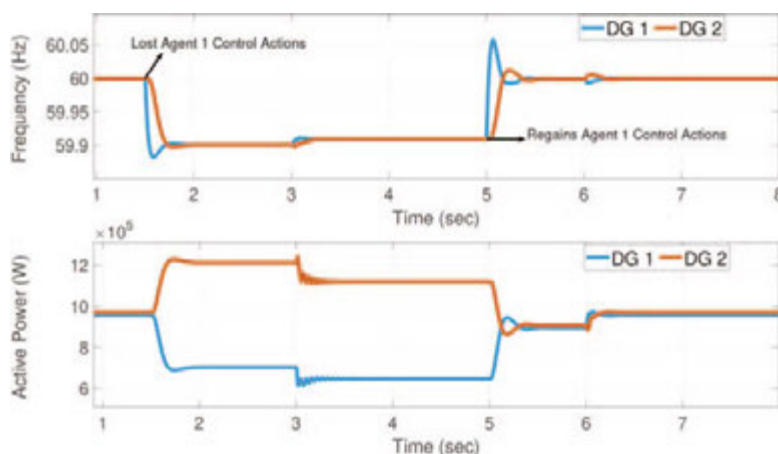
4. Conclusion and future recommendations

This study introduces a MADRL control approach, combined with traditional virtual synchronous generator (VSG) mechanics, to tackle major issues in microgrids reliant on inverters. The system concurrently focuses on four essential goals: (i) stabilizing frequency, (ii) maintaining voltage levels, (iii) ensuring precise active power distribution (with reduced APSE), and (iv) achieving accurate reactive power allocation (with lowered RPSE).

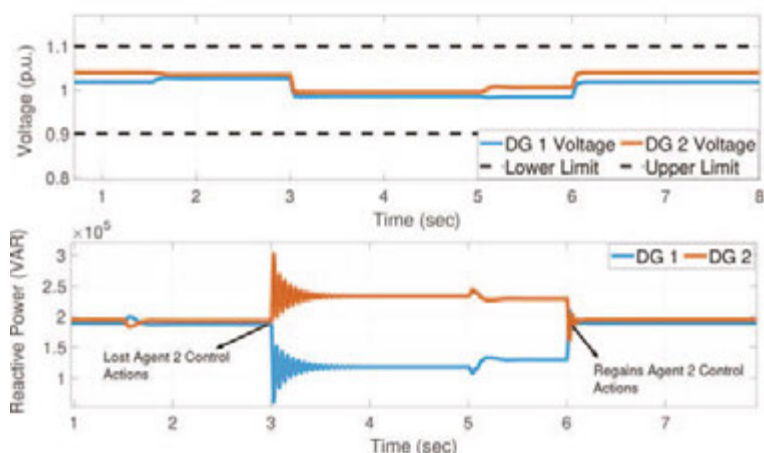
The approach operates without an explicit mathematical model, depending entirely on on-site sensor readings and eliminating the requirement for detailed mathematical representations of the microgrid. Agents undergo training via the DTDE technique to create completely autonomous decision-making rules. Incentive structures are thoughtfully crafted to direct each agent in fulfilling its unique management aims.

The effectiveness of the MADRL-based control strategy is validated through comparison with traditional VSG control and VSG enhanced with PI-based frequency restoration. The results demonstrate the superior capability of the proposed method in achieving all four objectives under varying load conditions and feeder impedance mismatches.

While the proposed MADRL-based strategy demonstrates strong performance in achieving frequency regulation, voltage stability, and accurate power sharing, it is important to acknowledge its current limitations. In this work, the agents are trained offline over a broad set of disturbance scenarios and subsequently deployed for online



(a) Active power and frequency redundancy.



(b) Voltage and reactive power redundancy.

Figure 8.
 MADRL performance under redundancy tests.

operation. This offline–online gap limits the agents’ ability to adapt to unforeseen operating conditions in real time. Future work should therefore focus on developing online reinforcement learning approaches, such as transfer learning or lifelong deep reinforcement learning, which can enable continuous adaptation and improve the plug-and-play capability of the agents without requiring complete retraining.

Another limitation lies in the scope of the validation. The framework has thus far been tested on relatively small microgrid systems, and its scalability to larger network model consisting of detailed generation sources models such as: wind, photovoltaic, and diesel generation remains an open challenge and paves a path for future research opportunity.

Finally, further research should extend beyond simulation-based studies. Promising directions include hardware-in-the-loop (HIL) experiments to validate real-time feasibility and comprehensive evaluations of cyber-physical resilience, ensuring robustness against communication delays, measurement errors, and potential cyberattacks.

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Section 4

Security, Resilience, and Integrity of Smart Grid Operations

Anomaly Detection and State Estimation Integrity Preservation in the Smart Grid

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Rubén Ruiz-Torrubiano and Deepak Dhungana*

Abstract

The integration of Information and Communication Technology (ICT) in Electric Power Systems (EPS) enhances monitoring and control. Critical infrastructures (CIs) such as SCADA and wide area monitoring systems (WAMSs) play a key role in grid security. Applications like state estimation (SE) ensures system awareness, supported by synchrophasors such as phasor measurement units (PMUs) for monitoring. However, attackers exploit ICT vulnerabilities to manipulate PMU measurements, misleading SE and triggering incorrect control actions. Therefore, aiming to deploy our model in CIs, we purpose using several lightweight statistical anomaly detection methods (e.g., median absolute deviation (MAD), cumulative sum—CUSUM, Kullback-Leibler divergence—KLD) for anomaly detection and purpose a model for preserving SE integrity by mitigating the effect of attacks on SE.

Keywords: wide area monitoring system, state estimation, phasor measurement units, anomaly detection, smart grid security

1. Introduction

The integration of Information and Communication Technology (ICT) into Electric Power Systems (EPSs) enhances their monitoring and control capabilities. A key application of ICT in this context is to provide *situation awareness* regarding the operational state of the EPS. This can be achieved through the deployment of a wide area monitoring system (WAMS), which consists of distributed sensors that capture system state data and communication infrastructure that transmits this information to a control center. The data collected by a WAMS supports real-time decision-making by system operators, for example, response to faults, and contribution to effective grid planning.

A significant technological advancement in the recent years is the development of *phasor measurement units (PMUs)*. These devices provide high-frequency measurements (typically at 50 Hz) of key power system parameters, for example, voltage, power, and phase angle that enable real-time situation awareness. PMU data can be transmitted over wide-area networks to the control center using specialized

communication protocols like IEC 61850. An important use of the PMUs data is for estimating the state of the power system, for example, where there is a lack of monitoring capability available or to mitigate measurement noise. Various techniques exist for state estimation (SE). A widely used academic approach is to use Kalman filters, which have been shown to be robust.

While the integration of ICT into power grids has led to smarter and more responsive systems, it can potentially introduce new security vulnerabilities and increase the risk of cyber-attacks. This increased risk stems from both the growing likelihood of cyber intrusions and the potentially severe consequences they may cause. For instance, in 2015, a nation-state cyber-attack in Ukraine triggered a regional blackout. Similarly, attacks targeting WAMS could have significant consequences: In the short term, if WAMS data is used for fault isolation, compromised data could lead to incorrect switching actions; in the long term, if the data informs grid planning, it could result in suboptimal and/or costly investment decisions.

In Cyber-Physical Systems (CPS), cyber-attacks can directly impact physical components. The visibility and cost of such attacks vary depending on the techniques employed. Compared to physical attacks, cyber-attacks are often easier to execute and offer several advantages, such as remote access, scalability, and reduced risk to the attacker [1]. As a result, cyber-attacks are more attractive to an adversary than physical attacks.

A critical class of attacks on WAMS is *false data injection (FDI)* attacks, in which an attacker manipulates data such as voltage or power measurements to mislead the systems and processes that rely on it. For instance, manipulated data can cause inaccuracies in the estimated state, leading to the adverse effects discussed earlier. Notably, researchers have identified that a subset of FDI attacks that are unobservable to standard bad data detection techniques are typically designed to identify anomalies caused by measurement noise. It has been shown that these unobservable attacks can result in significant consequences to an EPS.

An anomaly can be caused due to faults or attacks. For instance, a system fault can be induced due to a fake fault introduced by an attacker or a real fault (e.g., old and noisy sensor) in the system. Thus, an analysis of a system's behavior helps us to detect the cause of faults and attacks. Similarly, a transient in a power system can also cause an anomaly. Such a transient can be detected analyzing the dynamic behavior of the system with respect to its context or system information.

Abnormal behavior can be detected by analyzing different characteristics. Therefore, data-driven methods can detect various anomaly types by analyzing these different characteristics. Anomaly detection and the application of mitigation strategies (e.g., correction of manipulated data) help mitigating the effects of FDI attacks in monitoring and controlling applications (e.g., in SE).

In this work, we present an approach for mitigating the effect of FDI attacks on SE by applying a mitigation strategy after anomaly detection. This chapter is structured as follows: First, we present an overview of the related work in Section 2, second we discuss preliminaries in Section 3, then the proposed approach in Section 4, and the conclusion in Section 5.

2. Related work

The power grid's transformation into a decentralized cyber-physical ecosystem has created new attack surfaces across traditional, smart grid, and EV charging domains.

Accordingly, defensive strategies for anomaly detection have evolved to meet these distinct challenges [2].

In traditional power grids, defenses evolved from early bad data detection, which was vulnerable to false data injection attacks (FDIA) [3], to context-aware algorithms that distinguish malicious attacks from benign grid changes [4]. Other research has focused on model-agnostic methods to identify attacks during system transients [5] and robust Kalman filters that make the state estimation process itself more resilient to data and model uncertainties [1, 6]. Furthermore, the smart grid's expanded attack surface and privacy risks motivated a shift to distributed architectures like federated learning (FL) for collaborative detection without sharing raw data [2, 7]. Research is also advancing on hardening these AI models through Explainable AI (XAI) [8] and developing specialized Generative Adversarial Networks (GANs) to better distinguish sophisticated FDIAs from genuine physical faults in microgrids [9]. On the other hand, more recent EV charging frontier requires holistic security, such as enforcing cyber-physical consistency between digital commands and physical power data [10]. Research focuses on using TinyML for on-device detection on resource-constrained hardware [11], developing frameworks to counter coordinated charging attacks and even using GANs to proactively estimate the duration of an ongoing cyber-attack [9, 12, 13]. The ongoing research on anomaly detection demonstrates a necessary progression from isolated, reactive detection toward integrated, proactive security architectures that are intelligent, private, and context-aware. **Table 1** categorizes the

Author-year	Mitigation and comm. type	Technology/methodology	Situation type	Targeted anomaly/attack
Paudel 2024 [14]	AD, SE (PMU)	Lightweight statistical methods (MAD, KLD, CUSUM)	Voltage manipulation	False data injection (FDI) attacks.
Jithish et al. 2023 [7]	AD, aggregation (smart meter)	Federated learning (FL)	Not specified	False data injection attacks (FDIAs).
Aljohani and Bretas 2021 [15]	AD, SE	Bi-level optimization model	Parameter corruption	Cyber-attacks on system parameters.
Nandanoori et al. 2020 [5]	AD (PMU)	Model-agnostic (Koopman modes)	System transients	FDI attacks during system transients.
Maiti and Dey 2024 [16]	AD, SE	Deep reinforcement learning (DRL)	Not specified	Cyber-physical attacks.
Liu et al. 2011 [3]	AD, SE	BDD analysis, Jacobian manipulation	SE corruption	Unobservable FDI attacks.
Paudel et al. 2017 [1]	Attack modeling (PMU/WAMS)	Attack trees, threat modeling	Not specified	Advanced persistent threats (APTs).
Sanjab and Saad 2015 [17]	SE (defense strategy)	Game theory	Not specified	Smart grid data injection attacks.
Niddodi et al. 2019 [10]	AD (EV charging)	Cyber-physical consistency checks	EV charging	Cyber/physical state inconsistencies.
Padin et al. 2017 [18]	AD (home-area network)	Practical diagnostic framework	Home-area networks	False data injection attacks (FDIAs).

Table 1.
Relevant works on anomaly detection and mitigation techniques in smart grids.

key attributes of the relevant papers based on mitigation and communication types. The abbreviations are expanded at “Abbreviations” section.

3. Preliminaries

PMU measurements are used for estimating the states of a power system. Data integrity attacks on PMU measurements can lead to wrong estimated states. We assume that an attacker does not want to exceed any safety limits to cause immediate action but rather wants to poison the measurement data. This poisoning can aim at influencing historical data for planning, post-incident analysis, etc., influencing the state estimation or also preparing an attack, for example, by poisoning the “new normal,” so that those data points would be taken next time as reference.

3.1 False data injection attacks

The integration of ICT enhances the intelligence of power systems but also increases their susceptibility to cyber-attacks. Exploiting technological vulnerabilities, attackers can execute sophisticated or stealthy cyber-attacks, targeting Smart Grid Critical Infrastructures such as SCADA, which are deployed for communicating critical information. PMU measurements play a crucial role in estimating power system states. However, false data injection (FDI) attacks on these measurements can result in incorrect state estimations. For instance, voltage manipulation attack, a type of FDI attack on PMU measurements, can be executed using various techniques. Additionally, an APT can be implemented combining multiple cyber-attacks. The following paragraphs outline examples of voltage manipulation attacks.

Faulty sensor: An attacker is able to randomize voltage signal such that it looks like the signal is from a faulty sensor. If the signal is from a faulty sensor, measurement from the sensor is discarded until an operator repairs/changes the faulty sensor. If attackers can compromise multiple sensors in the network at the same time then measurements from multiple sensor will be discarded to avoid noise, in this case the estimator will not be able to estimate the state correctly.

Potential overvoltage: An attacker is able to add noise and slowly increasing offset in voltage signal such that the changes in the voltage signal is not visible due to noise. In this case, the potential overvoltage situation pretends to be normal by hiding in noise. Considering the voltage values for state estimation then induces incorrect states of the system.

Overvoltage: An attacker slowly increases offset in the voltage signal and is able to bypass the deployed anomaly detection technique. The manipulated voltage is fed to the estimator, which then estimates incorrect states on the basis of the manipulated voltage values. As a consequence, Control Center operators trigger protection actions against the incorrect estimated state.

Phase drift: An attacker can drop synchrophasor packets while transferring *via* a communication network. Consequently, the information is apparently unavailable from the network for a certain time due to network failure. Phase drift can be caused by the disconnection and reconnection of a network.

3.2 Anomaly detection methods

Machine learning: Machine learning has become a cornerstone for detecting anomalies in smart grid state estimation, with research rapidly advancing across several key

fronts. Foundational approaches utilize reconstruction-based models like deep autoencoders, which learn the patterns of normal grid operation and flag deviations. For instance, Afzal et al. [19] demonstrate this by applying an autoencoder to detect intrusions in energy communities, also extending the concept to a privacy-preserving federated learning framework. Building on this, generative models like the Generative Adversarial Networks (GAN) and Convolutional Neural Networks (CNN) are used to learn the entire distribution of normal data, enabling the detection of more subtle anomalies in residential consumption patterns [12]. The trend toward more sophisticated sequential models is exemplified by He et al. [20], who developed a hybrid architecture combining a bidirectional temporal convolutional network with a bidirectional gated recurrent unit (A-BiTG) to specifically target stealthy false data injection attacks by capturing complex temporal dependencies.

While early models were trained on centralized servers, the push for privacy and scalability has led to federated learning, as explored by Jithish et al. for distributed anomaly detection [7]. This paradigm allows multiple clients to train a global model collaboratively without sharing sensitive raw data. An emerging and even more advanced trend is the move toward interactive and autonomous defense systems. Maiti et al. [16] pioneer this shift by using a deep reinforcement learning framework, where an intelligent agent is trained not just to detect but to actively respond to cyber-physical attacks in real time. This progression highlights a clear trajectory in the field toward creating more intelligent, adaptive, and distributed security systems that can address the complex, evolving threats facing modern smart grids.

Lightweight statistical methods: Different FDI attacks on PMU measurements can be detected by analyzing different data features. We investigate the characteristics of important and distinct methods for detecting FDI attacks on Smart Grids. Our main goal is to detect different types of attacks. A single method may not detect all types of attacks or may not perform best for all attack types. A combination of different methods may help to improve anomaly detection performance and enable them to detect different attack types. We have chosen to apply simple statistical methods, in contrast to, for example, machine learning-based approaches because (i) we believe that they are sufficient to detect our proposed attacks, (ii) to promote the understanding of the results they produce—a desirable property for use in a critical infrastructure setting, such as power distribution networks, and (iii) to keep computational overhead small.

Further, considering the computational overhead in the critical infrastructure, we make a selection of lightweight algorithms as they can be deployed and executed with limited resources and memory. Well-established lightweight statistical methods like median absolute deviation (MAD) [21, 22], Kullback-Leibler divergence (KLD) [23, 24], and cumulative sum (CUSUM) [25] are applied for anomaly detection in Critical Infrastructure. A lightweight combination method, such as weighted voting [26], is used for combining the methods.

3.3 Methods evaluation

The evaluation of anomaly detection methods in smart grid state estimation hinges on four key areas [7]. The most fundamental is *detection accuracy* and *reliability*, which measures the correctness of a model's classifications. Rather than just overall accuracy, evaluations prioritize metrics that capture the security implications, such as the *Detection Rate* (or *Recall*) to ensure threats are caught and the *False Positive Rate (FPR)* to maintain system trust, which are critical in assessing resilience to false data injection attacks [3].

A second crucial area is operational efficiency and speed, which determines a method's viability for real-world deployment. For timely mitigation, key metrics include *Detection Delay*, which is the time taken to flag an anomaly, and *Throughput*, which measures data processing capacity. Furthermore, Computational *Complexity* and *Memory Footprint* are vital for assessing the feasibility of deploying algorithms on resource-constrained edge devices within the grid infrastructure [7].

Third, evaluations must consider system impact and robustness, moving beyond abstract detection to quantify the tangible consequences of an attack on the power system. Metrics such as *Mean Nodal Deviations* directly assess the integrity of the state estimation results, while others like the *Overload Factor* measure the physical stress on grid components. It evaluates the true resilience of the system and its protective schemes against cascading failures [27].

Finally, approach-specific evaluation is necessary as different methodologies have unique goals. For instance, *knowledge-based systems* are often assessed qualitatively on the *correctness* and *completeness* of their rulesets. Methods designed for root cause analysis are judged by their ability to accurately identify an anomaly's source, while hybrid models are evaluated on their ability to deliver synergistic performance improvements that surpass any single approach.

3.4 Mitigation strategy

Once an attack is detected, mitigation strategies focus on data correction, operational countermeasures, and proactive defense. These approaches aim to neutralize the impact of an attack and preserve the integrity of state estimation (SE). A primary strategy is the correction of manipulated data. This can involve advanced estimation algorithms designed to handle anomalies. For instance, a bi-level optimization model can be used to simultaneously identify and rectify malicious data injections targeting system parameters, integrating the correction process directly into the estimation algorithm [15]. Another approach uses an adaptive covariance Kalman filter, which can adjust to measurement deviations caused by attack vectors, thereby enhancing the stability of the SE process [6].

Beyond data correction, mitigation involves triggering control actions to counter the physical effects of an attack. Based on a trusted state estimate, system operators can deploy *Remedial Action Schemes* (RAS) to prevent cascading failures by re-dispatching generation or altering the network topology [27]. A different defense involves proactively altering the grid's configuration. By making secret, benign changes to the system, and the Jacobian matrix (H) used in SE is modified, which can expose an attacker's carefully crafted false data injection vector that relies on outdated system information [3].

Proactive and strategic defenses provide a more advanced layer of security. Game-theoretic models can be employed to analyze the interaction between an attacker and the grid operator, leading to optimal defense strategies that minimize the worst-case impact of an attack [17]. For dynamic threats, *deep reinforcement learning* (DRL) offers a powerful solution. DRL can be used to create autonomous defense agents that learn to detect and mitigate novel attacks in real time by observing the system's state and executing optimal countermeasures, moving beyond static or pre-programmed responses [16]. A practical framework for diagnosing attacks has also been developed for specific environments like home-area networks [18].

4. Approach

4.1 State estimation integrity

A state estimator estimates power system states based on observations. We use PMU measurements for SE using a DKF and estimate voltage states. If estimated voltage is normal, no reactions are needed to be triggered, and if the estimated voltage is under voltage or over voltage, then necessary protection actions need to be applied in the system.

When an attacker is able to manipulate voltage values, these manipulated voltage values are used for estimating states. Estimated states based on the manipulated values can be different than the real states of the system. **Table 2** shows possibilities how an attack can fake the system's states.

Due to the data manipulation attack, operators may trigger protection actions in the system based on the fake estimated states. Consequently, unnecessary actions are triggered in the system leading to critical condition. For example, if the system is in under voltage and fake state shows it is in over voltage, and then, reactions can lead the system to invoke wrong power control actions.

4.2 Voltage difference calculation

An attack can cause incorrect state estimations based on manipulated measurements, leading to the reporting of false voltage values to the control center. Our goal is to quantify the total voltage error reported to the control center due to an attack. To this end, we analyze the amount of unnecessary voltage reported to the control center with and without the use of an anomaly detection scheme.

Here, we aim to compute voltage in a discrete-time signal to assess the impact of an attack on data integrity and evaluate how anomaly detection schemes can help to preserve it. For discrete time signals, power (or energy) can be calculated by using summations instead of integrals [28]. For finite power (or energy), it is absolutely summable [29]. We consider the same definition for calculating the voltage amount over time. Therefore, here we can calculate the total amount of estimated voltage in normal operation scenario using Eq. (1).

$$S_{orig} = \sum_{i=1}^N |\hat{x}_{i|i}| \quad (1)$$

where i is a time instance.

Similarly, the total estimated voltage in an attack scenario can be obtained using Eq. (2).

Real state	Normal	Under voltage	Over voltage
Estimated state	Over voltage	Normal	Normal
	Under voltage	Over voltage	Under voltage

Table 2.
 Possibilities of fake states.

$$S_{attack} = \sum_{i=1}^N |\hat{\mathbf{x}}_{i|i,a}| \quad (2)$$

Figure 1 illustrates an example of estimated states under normal operation and during an attack. The area between the two curves represents the error reported to the operator due to the attack.

The area between the curves can be calculated using Riemann integral [31] as shown in Eq. (3).

$$area = \int_{t_0}^{t_f} (\hat{\mathbf{x}}_{i|i,a} - \hat{\mathbf{x}}_{i|i}) di \quad (3)$$

where attack starts at time t_0 and attack ends at time t_f .

By dividing the area into N rectangles of same width $\Delta i = \frac{t_f - t_0}{N}$, we can estimate area by Eq. (4) using Riemann sums [32, 33].

$$area \approx \sum_{i=1}^N (\hat{\mathbf{x}}_{i|i,a} - \hat{\mathbf{x}}_{i|i}) \Delta i \quad (4)$$

Approximation of an area for a finite number of data points can be calculated using the approximated summation of area using Riemann sums [31], and exact area can be calculated if $\Delta i \rightarrow 0$ as shown in Eq. (5) [31].

$$area = \lim_{\Delta i \rightarrow 0} \sum_{i=1}^N (\hat{\mathbf{x}}_{i|i,a} - \hat{\mathbf{x}}_{i|i}) \Delta i \quad (5)$$

We can use Eq. (5) to calculate area between the curves. Thus, total difference of estimated voltages in normal operation and in an attack scenario over time can be calculated using Riemann sums as shown in Eq. (6) as in Refs. [32, 33].

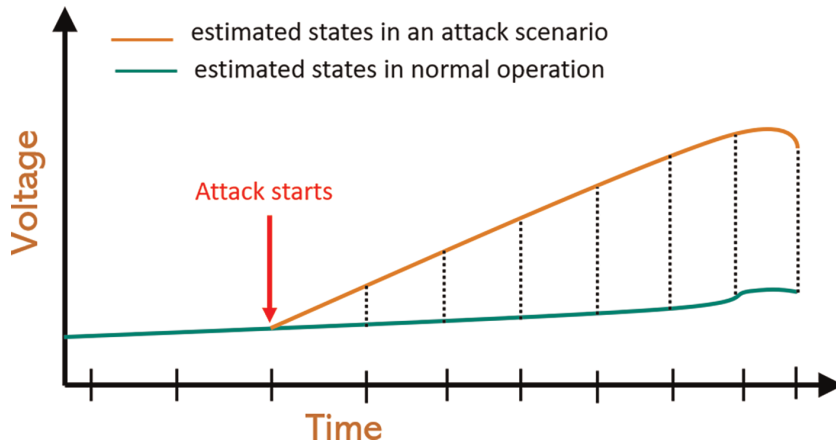


Figure 1.
An example figure of estimated states in normal operation and in an attack scenario (source: [30]).

$$S_{err} = \sum_{i=1}^N |\hat{\mathbf{x}}_{i|i,a} - \hat{\mathbf{x}}_{i|i}| \quad (6)$$

where time interval between two consecutive data points is constant.

We use the sum of errors caused by an attack (S_{err}) as a metric to measure the difference between reported and original values. This metric helps evaluate the effectiveness of our method in preserving state estimation integrity. Calculation of the unnecessary energy or voltage is crucial, as it can trigger protective actions like load shedding or power control. Therefore, we focus on maintaining state estimation integrity by replacing detected anomalous states with the predicted values. The role of anomaly detection methods in preserving state estimation is discussed in the following section.

4.3 Preservation of estimated state integrity

The system's condition is assessed based on its estimated states. Operators at the control center rely on this information to initiate appropriate control actions. Therefore, our goal is to enhance the trustworthiness of these estimates by detecting and correcting anomalous data before it reaches the estimator.

Detected anomalous data are replaced with predicted values that are referred to as corrected values. These corrected data are then sent to the state estimator for improving the trustworthiness of the estimated states. The “corrected” value differs from the “correct” value (which is the actual measurement). Corrected voltage value is represented by Eq. (7).

$$\mathbf{z}_{k,c} = \hat{\mathbf{x}}_{k|k-1} \quad (7)$$

where $\hat{\mathbf{x}}_{k|k-1}$ is the predicted value.

Estimated state using the corrected data is represented by Eq. (8)

$$\hat{\mathbf{x}}_{k|k,c} = \mathbf{H}\hat{\mathbf{x}}_{k|k-1} + \mathbf{L}_k(\mathbf{z}_{k,c} - \mathbf{H}\hat{\mathbf{x}}_{k|k-1}) \quad (8)$$

Figure 2 illustrates the state estimation process at a time step k considering the anomaly detection and bad measurement replacement (or correction) scheme. Current state is predicted (denoted as $\hat{\mathbf{x}}_{k|k-1}$) from the previous estimated value $\hat{\mathbf{x}}_{k-1|k-1}$. Let's us assume an attack starts at time step k and is detected immediately at the time step k . Then, the manipulated measurement at time step k $\mathbf{z}_{k,a}$ is replaced by the predicted value $\hat{\mathbf{x}}_{k|k-1}$, and the corrected value is denoted as $\mathbf{z}_{k,c}$. A corrected estimated state at time step k (denoted as $\hat{\mathbf{x}}_{k|k,c}$) is estimated from the predicted value $\hat{\mathbf{x}}_{k|k-1}$ and the corrected measurement $\mathbf{z}_{k,c}$. Thus in next time step $k+1$, state is predicted from $\hat{\mathbf{x}}_{k|k,c}$ and the estimation process continues considering corrected data and correct prediction.

The area between estimated voltage states during attack and estimated voltage states after replacing malicious measurements represents the amount of unnecessary voltage not reported to an operator due to the deployment of anomaly detection method. Area under the curves can be calculated using Eq. (9).

$$S_p = \sum_{i=1}^N (\hat{\mathbf{x}}_{i|i,m} - \hat{\mathbf{x}}_{i|i,c})(t_{i+1} - t_i) \quad (9)$$

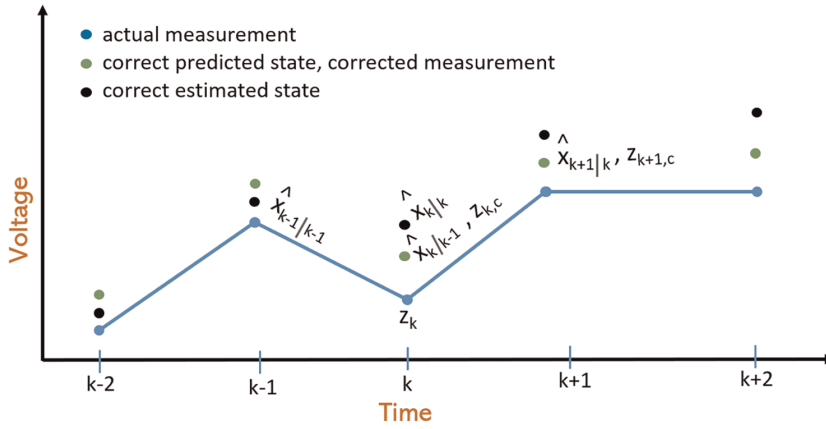


Figure 2.
State estimation process considering anomaly detection and corrected measurement.

where N is the number of partition of area between the curves, and t is time unit.

The total voltage (sum after anomaly detection and replacement of anomalous data (ADR)) reported to the operator after deploying anomaly detection method together with bad measurement replacement can be calculated using Eq. (10).

$$S_{ADR} = \sum_{k=1}^N |\hat{x}_{k|k,c}| \quad (10)$$

where k is a time instance.

The amount of the error while reporting the voltage to the control center can vary depending on the anomaly detection methods' detection delay but also since the corrected value may differ from the original measurement. Therefore, the sum of the errors after correcting the value can be calculated using Eq. (11).

$$S_{diff} = \sum_{k=1}^N |\hat{x}_{k|k,c} - \hat{x}_{k|k}| \quad (11)$$

4.4 Discussion

The application of the well-established lightweight statistical methods MAD, KLD, and CUSUM is presented in our previous work [14]. The piece of work illustrates the methods' detection performance for FDI attack types similar to those mentioned in Section 3. Therefore, here anomaly (attacks types—noisy sensor and (potential) overvoltage) detection performance of the methods (MAD, KLD, and CUSUM) are generalized based on our previous work [14], which is illustrated in **Table 3**.

The above-mentioned attack types were simulated on real power system data using MATLAB where anomaly detection methods were deployed. MAD performs well and fast for sudden increases. However, it fails for attacks that look like a faulty or noisy

Methods	Noisy sensor	(Potential) overvoltage
MAD	Highest precision, lowest FPR	Lowest FPR
KLD	MAD < Accuracy and Recall < CUSUM Precision < MAD, CUSUM	MAD < Accuracy and Recall < CUSUM Precision < MAD, CUSUM
CUSUM	Highest accuracy and recall	Highest accuracy and recall

Table 3.
Generalized anomaly detection performance comparison of MAD, KLD, and CUSUM in terms of accuracy precision, recall, and FPR.

sensor. KLD detects anomalies with some delay but then consistently detects subsequent anomalies. Detection delay varies a lot among methods and attack types. MAD picks up changes earlier than KLD or CUSUM. The combined method—weighted voting improved anomaly detection performance by capturing all attack types (including at least some anomalous data points), and achieved higher precision than individual methods by generating fewer false alarms.

Anomaly detection and state estimation integrity preservation under attack types are presented in Ref. [30]. Similarly, enhancement in the anomaly detection performance using combination and SE integrity preservation under attack types are presented [34]. The results illustrated in Ref. [34] depict that the amount of the unnecessary voltage in types of attacks vary on the detection delay of the detection methods. We applied the purposed approach in detecting anomalies against smart grid and mitigating their effects on state estimation in the smart grid. As the anomaly detection methods are data based, the application of the purposed approach can be applied in other domains.

5. Conclusion

We propose using lightweight statistical methods (e.g., MAD, KLD, CUSUM) for detecting anomalies in critical infrastructure in the smart grid. An application of several methods that analyze different characteristics can significantly improve the detection performance which influences in mitigating the effects of attacks on state estimation. Further, the combination method (e.g., weighted voting) enhances the detection performance. Therefore, we argue that a set of multiple different methods need to be deployed for detecting attack types. The detected anomalous data needs to be corrected for mitigating the effect of false data injection attacks on state estimation. Therefore, we propose a model for preserving the state estimation integrity by mitigating the effect of the false data injection attacks.

Simulation setup for experiment enables precise manipulation of the attacks to study cause-effect relationships and helped to identify bottlenecks and resource constraints. It is also useful for comparing the methods performance under consistent conditions. The simulation setup mentioned in this work was considering a desirable property for using in a critical infrastructure setting with few computational resources. This can also be applied to other application area considering their system environment.

Key abbreviations

AD	anomaly detection
SE	state estimation
PMU	phasor measurement unit
WAMS	wide area monitoring system
FDI/FDIA	false data injection/false data injection attack
Stat.	statistical
MAD	median absolute deviation
KLD	Kullback-Leibler divergence
CUSUM	cumulative sum
FL	federated learning
DRL	deep reinforcement learning
BDD	bad data detection
Manip.	manipulation
APT	advanced persistent threat
EV	electric vehicle

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Section 5

Market Design, Policy, and System-Level Enablement

Market Mechanisms and Policy Frameworks for Enabling Smart Grids in the Energy Transition

Xiaoxiao Yu and Jingrui Zhang

Abstract

This chapter explores the critical role of market mechanisms and policy frameworks in supporting the development of robust and intelligent smart grids, which are essential for the modern energy landscape. It delves into key strategies for building flexible and efficient electricity markets capable of accommodating the large-scale integration of renewable energy, ensuring energy security, and enhancing industry efficiency. Additionally, the chapter highlights the importance of coordinated policy support, including strategic planning, technological innovation, industrial upgrading, and financial mechanisms, all of which are crucial for fostering the sustainable evolution of smart grids. These elements collectively contribute to facilitating cross-border electricity trade and driving the global energy transition toward cleaner and more reliable energy systems.

Keywords: smart grid, electricity market, renewable energy integration, policy framework, energy transition

1. Introduction

This chapter adopts a conceptual and policy-oriented analytical approach, aiming to synthesize key elements of market mechanisms and policy frameworks in the context of smart grid development. While the analysis draws from international best practices and institutional frameworks, it does not employ empirical modeling or data-driven evaluation due to the strategic and forward-looking nature of the topic. As such, the findings should be interpreted as qualitative insights rather than statistically validated conclusions. Future research could complement this work with case-based or quantitative analysis to further assess the effectiveness of specific policy mechanisms.

2. Electricity market implementation

Electricity market mechanisms, built on the physical foundation of the smart grid, must reflect the principles of decarbonization, electrification, digitalization, and intelligence [1–3]. These mechanisms should not only follow market fundamentals but also accommodate the technical characteristics of power system operation [4].

Market designs must be adapted to local conditions—such as economic development, resource availability, and energy mix—to establish efficient, stable, and flexible pricing and trading systems. They should support the large-scale integration of renewable energy, allocate the cost of flexibility and balancing resources appropriately, and continuously improve mechanisms for transmission, feed-in, and retail pricing.

At the same time, greater coordination between electricity markets and other energy markets (e.g., gas, heat, and hydrogen) is needed to enable more efficient clean energy deployment and support the sustainable growth of global power trade.

2.1 Key mechanism

2.1.1 Establishing multi-timescale trading mechanisms integrate long-term and spot markets

On the generation side, electricity markets should be designed to effectively link long-term and spot market mechanisms. Following the principles of using long-term contracts to hedge risks and spot markets for price discovery, countries should develop integrated frameworks that allow these two market layers to interact seamlessly. As market reforms deepen, it is critical to establish a rational, interactive pricing mechanism that reflects supply-demand dynamics.

Long-term markets should support continuous daily operation while accommodating centralized bidding and rolling matching across multiple timeframes, such as annual, quarterly, monthly, weekly, and daily intervals. In parallel, curve-based contracts should be introduced to align long-term transactions with spot market intervals, breaking contracts into temporal curves to match demand and generation more dynamically. This evolution marks a transition from traditional grid-wide balancing to price-based curve matching between generation and load.

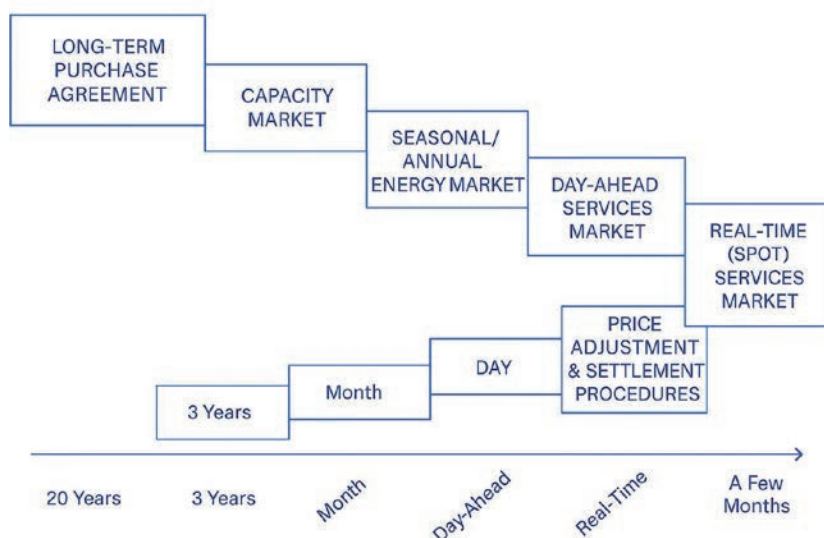


Figure 1.
Illustration of multi-time level electricity market.

On the network side, transmission and distribution (T&D) pricing mechanisms should be reformed to better reflect grid operational capabilities and to ensure the efficient allocation of renewable energy. A robust T&D tariff framework should encourage proactive grid operation, based on fair allocation of rights and responsibilities among market participants.

With the large-scale deployment of renewables, grid investments and operating costs—including interconnection projects, grid expansion, and smart technologies—are rising. T&D tariffs should be calculated based on actual costs borne by users at different voltage levels, while incorporating reasonable returns for network operators. Moreover, tariffs should be aligned with upstream generation prices, line loss discounts, system operating costs, and downstream retail prices to ensure consistency across the electricity value chain. Transparent and science-based price regulation will enhance the rationality of T&D pricing and position the grid as the central coordinator for power-source, grid, load, and storage integration (**Figure 1**).

2.1.2 Improving ancillary service mechanisms

With the increasing share of variable renewable energy (VRE), power systems face heightened requirements for frequency stability, transient overvoltage control, system inertia, steady-state voltage support, and reserve capacity [5]. To address the operational challenges of large-scale VRE integration, a comprehensive and diversified ancillary services market must be established.

Countries should tailor auxiliary service offerings to their resource endowments, energy mix, and market maturity [6]. This includes expanding service types to cover active and reactive power balancing, emergency restoration, inertia response, ramping capability, automatic voltage control, phase angle regulation, and black-start services. A well-structured ancillary services market will encourage conventional generators to shift toward flexible support roles and facilitate the participation of new resources such as energy storage, controllable loads, and electric vehicles. Incentive policies and market signals should be leveraged to unlock demand for ancillary services, increase market liquidity, and strengthen their critical role in system stability [7].

2.1.2.1 Establish a cost allocation mechanism for ancillary services in the context of power system transformation

As traditional baseload generation gives way to flexible and responsive power sources, market pricing mechanisms must evolve. With rising VRE penetration, the per-unit cost of ancillary services is increasing, necessitating a scientific and equitable cost-sharing model. Following the “beneficiary pays” principle, clear guidelines should be developed for identifying responsible parties, defining cost-sharing ratios, setting payment ceilings, and applying rules for inter-zonal cost allocation.

In the early stages of market development, ancillary service costs may be shared between generation-side entities and market-based users. As markets mature, more granular allocation coefficients should be introduced based on generation type and operational characteristics, with progressive removal of cost-sharing caps and dynamic adjustment of contribution ratios. Efficient price signals will help distribute costs fairly and maximize service efficiency under least-cost principles.

2.1.2.2 Design ancillary service mechanisms to enhance system flexibility

To address increasing volatility and uncertainty in power systems, priority should be given to ancillary services that strengthen inertia, improve frequency regulation, and ensure reactive power and voltage control. Markets should classify services by response and duration requirements, enabling tailored support across different timescales.

A broad range of flexible resources—including storage systems, demand response, and EVs—should be incentivized to participate in these markets. A robust pricing mechanism is essential to reflect the real-time value of flexibility and encourage timely and voluntary participation. Grid operators should take charge of procuring and managing ancillary services, ensuring their integration into system operations. Regional and cross-border ancillary services should also be promoted through joint bidding and cooperative mechanisms, reducing trade barriers and enabling efficient allocation of flexibility resources across jurisdictions.

2.1.3 Building capacity adequacy mechanisms

2.1.3.1 Develop tailored mechanisms to ensure generation adequacy

Given the intermittent and variable nature of renewable energy, power systems must secure adequate dispatchable and controllable capacity to ensure long-term reliability. Countries should adopt capacity adequacy mechanisms suited to their market structures, resource conditions, and development levels.

A variety of mechanisms are available, including scarcity pricing, capacity markets, capacity remuneration schemes, and strategic reserves. In mature markets, scarcity pricing and capacity auctions may be preferred. Scarcity pricing encourages rapid response to market signals, while capacity markets enhance investment transparency through competitive bidding. For less developed markets, capacity compensation mechanisms may serve as a transitional measure, ultimately leading to resource-neutral, competitive capacity markets. Price signals from these mechanisms are essential to guide investment and maintain stable, long-term adequacy.

2.1.3.2 Ensure alignment between capacity mechanisms, planning, and market design

Effective capacity mechanisms must be coordinated with system planning and broader market rules to prevent both underinvestment (risking reliability) and overinvestment (leading to inefficiency). National and regional planning frameworks should assess capacity requirements based on available resources and transmission capabilities, setting realistic investment targets and resource portfolios.

Market design must clearly define the interactions among capacity pricing, energy prices, and ancillary service costs. A well-functioning market will ensure that capacity costs are accurately embedded in market-clearing prices. Transparent information disclosure is also vital. Real-time and rolling assessments of system adequacy, published price forecasts, and capacity availability metrics can support investment decisions and facilitate efficient competition in capacity provision.

2.1.4. Develop a dispatching and trading mechanism to promote cross-border and cross-regional power flow

Establish a cross-border and cross-regional transmission capacity allocation mechanism based on the situation. To promote the construction of cross-border and cross-regional power grids, it is necessary to properly solve key issues such as transmission channel capacity allocation, transmission cost recovery and power transaction connection between different countries and electricity markets. Based on resource endowments and electricity market development conditions, building a reasonable cross-border and cross-regional transmission capacity allocation mechanism will help promote the efficient circulation of power resources between countries and regions. For priority power generation plans and special projects signed between countries and regions based on annual or multi-year cycles, the transmission rights of transmission channels should be prioritized, and transmission fees should be paid in advance through contractual agreements to lock in profits. For cross-border and cross-regional power transactions in the medium and long term and spot markets, the explicit auction mechanism should be used to allocate transmission capacity in combination with different transaction time sequences (year, quarter, month, day before, and day), or a “first come, first served” capacity allocation strategy should be implemented according to the contract period. With the continuous improvement of market coupling, the explicit auction mechanism should be gradually promoted to achieve more transparent and efficient capacity allocation. In the case of highly coupled markets and the direction of the cross-border transmission channel flow is no longer fixed, for transactions participating in the cross-border electricity spot market, the implicit auction method of centralized optimization scheduling can be used to allocate transmission capacity and automatically match cross-border transactions with transmission channel capacity. The revenue and congestion surplus generated by the auction will be used to cover the investment, operation, and maintenance costs of cross-border and cross-regional transmission projects to ensure the sustainable development of the transmission system.

Design a transaction clearing model to promote the development of market coupling. The improvement of the intelligent capacity of the power grid provides a solid technical and hardware foundation for cross-border and cross-regional market coupling. A price coupling mechanism covering multiple countries should be established to achieve real-time adjustment of the supply and demand of various countries' markets, and reduce the balancing scheduling costs of local markets with the help of a wider range of market coupling, so as to maximize the overall social welfare. This coupling mechanism comprehensively considers the quotations of market members, physical power grid parameters, and operating status, relies on the synchronous collection of power grid data and intelligent computing capabilities, quickly optimizes calculations, and uniformly determines the clearing results of various countries' markets. Market coupling is based on the joint dispatch of the entire network, and jointly clears the supply and demand of various countries and cross-border transmission capacity to form a unified power generation and consumption plan for the next day and the same day. If some countries are unable to participate in the unified clearing due to grid structure or technical conditions, these countries will implement local separate transaction clearing. Energy transactions and transmission capacity transactions are optimized and cleared simultaneously, effectively improving the efficiency of transmission resource allocation and avoiding problems such as conflicts in the direction of the flow. The unified market-clearing price not only reflects the dual value of transmission capacity

and electric energy, but also provides accurate price reference signals for other market transactions, promoting the overall healthy development of the market.

Scientifically and reasonably formulate a market real-time balancing mechanism. To ensure the real-time balance of the transnational power system, it is necessary to establish a balancing management mechanism that conforms to the development stage of the national and regional markets. Through diversified means, the decentralized and open market operation and systematic centralized dispatching are effectively connected to reflect the system supply and demand status and balance costs in real time, and continuously improve the economic efficiency of system operation. In the early stage of marketization, it is advisable to adopt a system with a real-time balancing mode dominated by grid dispatching, and ensure real-time supply and demand matching through a pre-listing balancing mechanism and deviation assessment. As the market matures, a balancing mode combining physical regulation of electric energy with the ancillary service market can be promoted. The ancillary service market is independent of the electric energy market, and the transaction is cleared by the grid. Market members can adjust their bids up and down in the regulated electric energy market to improve the flexibility of regulation resources. Furthermore, a balancing unit can be constructed to coordinate market players to participate in the operation and regulation. By clarifying the division of balancing responsibilities, the complementary and mutual assistance of multiple power sources and loads within the unit can be formed, providing a more controllable management object for the overall dispatch of the power grid. In addition, for the highly market-oriented stage, a balancing mechanism of integrated trading and joint clearing can be implemented, with the power grid responsible for real-time dispatch and market organization, and advanced algorithm optimization based on market members' quotations and costs, and joint clearing of balancing resources such as electricity, frequency regulation and standby, to minimize overall operating costs and maximize economic benefits.

2.2 Development path

2.2.1 Current status of electricity market development

Globally, electricity market development is progressing at varied paces across different regions, shaped by national priorities, institutional maturity, resource endowments, and infrastructure readiness. While some advanced economies have established sophisticated multi-level market systems with high renewable integration, many developing regions remain in the early stages of market liberalization. Cross-border electricity trade, ancillary service reform, and flexible market design have emerged as common themes, yet the specific approaches and outcomes vary significantly. The following regional examples illustrate the diversity of market mechanisms and policy responses in the smart grid transition:

Europe: The European Union's Internal Electricity Market provides a mature example of cross-border market coupling and implicit transmission capacity auctions, as seen in the Nordic-Baltic and Central-Western European regions. Regulatory harmonization by ENTSO-E supports high renewable penetration through integrated ancillary services.

China: China's electricity spot market pilots and regional interconnections have enabled large-scale integration of renewables, particularly through long-distance UHV transmission from western wind/solar bases to eastern load centers. Ancillary service reforms are underway to accommodate variability.

United States: Regional Transmission Organizations (RTOs) such as PJM and CAISO operate mature ancillary service and capacity markets, with differentiated

mechanisms tailored to grid topology and resource mix. For example, CAISO's flexible ramping product addresses solar-induced variability.

Africa: In Sub-Saharan Africa, market-based reforms are at an early stage. However, regional power pools such as the Southern African Power Pool (SAPP) offer lessons in gradual liberalization, supported by donor-driven infrastructure investments and pilot cross-border trades.

Latin America: Many countries in Latin America, such as Brazil, Chile, and Mexico, have implemented electricity market liberalization with varying levels of success. Brazil operates a centralized market with long-term energy auctions and robust demand forecasting mechanisms. Chile, an early mover, has a competitive generation market and is pioneering nodal pricing and green certificate trading to facilitate renewable deployment. Cross-border interconnections are limited but gaining attention, particularly in the Andean and Southern Cone regions.

Middle East and North Africa (MENA): The MENA region shows growing momentum in renewable energy deployment and electricity market reform. Countries such as Morocco and Jordan have introduced auction-based procurement and grid code updates to enable private participation. The Gulf Cooperation Council (GCC) Interconnection Authority provides a platform for regional electricity trade, though market coupling remains nascent. Policy frameworks are increasingly integrating flexibility services and tariff restructuring.

Southeast Asia: Electricity market development in Southeast Asia varies widely. Singapore operates a fully liberalized wholesale electricity market, with real-time nodal pricing and demand-side participation. Thailand and the Philippines are progressing toward competitive markets, including capacity and ancillary service mechanisms. The ASEAN Power Grid initiative is fostering cross-border trade and infrastructure integration, though implementation is uneven across member states.

2.2.2 Mechanism construction

The construction of the electricity market mechanism shall be innovative and improved. Relying on the powerful configuration capability of smart grids, a multi-level competitive wholesale market based on electricity spot shall be effectively established. Renewable energy generation would become the absolute main force of market transactions. The market price signal based on the price of renewable energy electricity spot products could be efficiently transmitted to the user side, giving full play to the role of promoting the consumption of new energy; green certificates, green electricity transactions and carbon market transactions shall be fully integrated, and the comprehensive intelligence of the power grid could promote the real-time traceability of green electricity in seconds, guide the real-time consumption of clean electricity, and the development of green certificates and green electricity transactions toward homogeneity. The carbon market shall complete its incentive effect on emission reduction in the power industry, and its functional positioning would shift to guiding the substitution of electricity in energy-intensive industrial sectors; the auxiliary service market shall be highly integrated with the spot market, and the development of power grid operation and dispatching technology would promote the continuous innovation of the auxiliary service business model. As the capacity market and the scarce electricity price mechanism gradually mature, the integrated business model of renewable energy and energy storage would be sound and complete, and energy storage would be efficiently applied in the generation, transmission, distribution and use links (**Figure 2**).

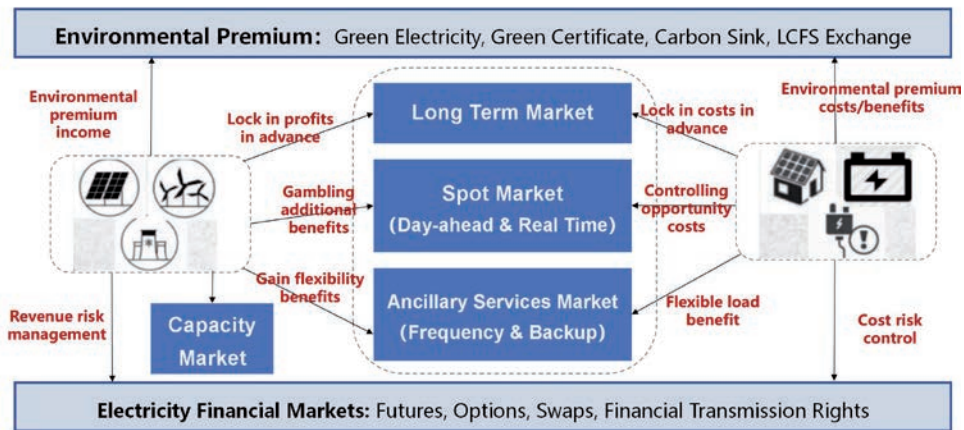


Figure 2.
Illustration of electricity market mechanism of future smart grid.

2.2.3 Market transactions

The participating entities are diversified, the market competition is orderly, and the competition pattern has developed from unilateral bidding on the power generation side to more buying and selling on the power generation side, the transmission and distribution side, and the user side, forming a collaborative interaction model of multiple sources, networks, loads, and storage. The trading varieties are innovatively developed, short-term high-frequency trading has become the norm, quantitative trading is widely used, different types of trading varieties between markets are integrated, power trading automatically includes the environmental attributes and carbon emission reduction attributes of clean energy, the degree of power financialization is strengthened, and power derivatives are greatly enriched, promoting market prosperity. The trading level has been greatly improved, and the application of highly intelligent and information-based technologies has promoted the development of trading toward full-time scale and high-frequency trading. The closing time of continuous trading is constantly approaching real-time, the scope of market coupling is constantly expanding, and the coordination of network and source is more sufficient, realizing the real-time consumption of clean energy on a large scale.

3. Policy system

Supporting policies provide institutional guarantees for the construction of smart grids. We should strengthen policy guidance, promote institutional and mechanism innovation, strengthen the systematic, holistic and coordinated nature of policy measures, and establish a sound policy guarantee system. Lead the development of power grid construction through reasonable planning, promote the effective market and effective government to play their functions [8]; strengthen technological innovation and research and development, promote the extensive application of advanced technologies and high-quality development; effectively stimulate industrial investment, serve the upgrading of the industrial chain and green transformation; increase fiscal and financial support, and create a good business investment environment.

3.1 Strategic planning

3.1.1 Coordinated planning of power sources and grids

Enhance coordination between power supply and grid development. In the context of rapid new energy expansion, it is essential to align system regulation capacity, grid infrastructure, and new energy deployment to ensure efficient utilization. Strategic planning must bridge the supply and grid sides, accounting for mismatches in construction timelines and administrative boundaries. Energy authorities should develop rational construction schedules for supporting grid projects, coordinate new energy layout, commissioning timelines, and consumption directions, and integrate grid development with urban and land-use planning. Regular updates to power development plans should ensure synchronization between new energy projects and grid construction.

Based on targets for new energy capacity and utilization, energy authorities should establish annual development plans, assess system regulation requirements, and define enhancement strategies. Grid enterprises should expand transmission capacity for new energy, strengthen interregional support, and improve the observability, measurability, controllability, and flexibility of the grid, reinforcing its role as a resource allocation platform.

3.1.2 Integration of digitalization and intelligence

Accelerate the integration of digital and intelligent technologies in the power sector. Formulate dedicated plans for the digital and intelligent transformation of power grids, emphasizing their application in grid construction and across the broader power system [9]. Clarify development objectives, tasks, and policy safeguards to guide implementation.

Given the wide scope of the power system industrial chain, align digital development with national and regional plans to pool resources and promote deep integration. Prioritize the digital upgrading of core grid businesses through smart computing, coordination of transmission and distribution, structural reinforcement, and resilience improvement. Supportive policy frameworks should also cover digital energy technologies, green electricity, high-efficiency equipment, AI applications, smart end-use devices, integrated smart energy systems, and intelligent energy storage to drive comprehensive smart energy development.

3.1.3 Market mechanisms as a leading force

Leverage market mechanisms under the guidance of sound planning. Foster efficient resource allocation, steady grid expansion, and flexible resource mobilization. Establish electricity pricing systems tailored to national contexts, integrate grid dispatch with electricity markets, and enable cost pass-through to end users to support integrated development of generation, grid, load, and storage.

Advance diverse electricity markets—including medium- and long-term, spot, ancillary services, and capacity markets—and promote their coordination. Increase user-side participation from virtual power plants, electric vehicles, and interruptible loads, enhancing the value of flexible resources. Develop electricity and carbon markets compatible with high renewable penetration, improve incentives for green electricity and certificates, and recognize environmental value through market-based mechanisms. Aim to establish a safe, efficient, competitive, and well-governed market system.

3.1.4 Effective use of administrative regulation

Complement market development with robust administrative oversight. Address issues such as market inefficiencies and information asymmetries by balancing equity and efficiency through regulation. Strengthen supervision, align market mechanisms with governmental roles, and support orderly development.

Governments should refine market rules, standardize technical interfaces, optimize pricing mechanisms, and clarify responsibilities in trading, dispatch, and safety. Establish a regulatory framework covering market participants and institutions, define safety obligations, set entry and exit standards, and develop dispatch and settlement rules. Build systems for information disclosure and credit management to ensure fair access to grid services and equitable market participation.

3.2 Industrial development

3.2.1 Optimize and enhance basic industry policies

Strengthen policies supporting basic industries spanning power generation, transmission, storage, and system integration, such as grid construction, equipment manufacturing, and related upstream and downstream sectors. Build an energy infrastructure suited to high levels of renewable integration and multi-energy coordination to enable efficient resource allocation. Centering the power grid within the industrial chain, continuously improve policies on energy infrastructure, new energy development, technological innovation, renewable energy consumption, and grid connection pricing. Emphasize systematic, integrated, and coordinated policy design to foster a green, low-carbon, efficient, safe, and controllable power industry, while driving regional development and improving livelihoods.

3.2.2 Strengthen digital industry policies

Position data as a core resource and modern networks as key infrastructure. Promote the integration of next-generation information technologies—such as cloud computing, big data, IoT, mobile communications, AI, and blockchain—into the energy and power sector. Accelerate digital transformation across the grid's core areas: smart equipment, sensor networks, data platforms, and supply-demand coordination. Advance digital openness and cross-sector innovation, and establish supportive policies for digital infrastructure, intelligent applications, talent development, and related areas of investment, finance, and intellectual property. Guide the digital energy sector toward openness, interconnectivity, and intelligent efficiency.

3.2.3 Proactively plan for emerging industry policies

Anticipate and guide the development of emerging industries based on digital platforms to meet diverse energy demands. Promote new business models such as integrated energy services, electricity-carbon trading, power sector finance, and vehicle-grid interaction. Formulate policies supporting business innovation, fiscal incentives, energy-ICT integration, and market-based development to enable orderly growth. Explore the potential of the electricity-carbon economy and power finance sectors through investment incentives and financial tools to attract social capital, lower emissions, and enhance the grid's capacity for large-scale low-carbon energy

integration. Early policy planning in emerging sectors will foster innovation, inclusivity, and sound industrial governance.

3.3 Finance and taxation

3.3.1 Fiscal and taxation policies to support the healthy operation of smart grids

Establish a fiscal and taxation system aligned with the development needs of smart grids. Leverage fiscal policy to optimize the allocation of power supply and demand, promote technological innovation in the power industry, reduce the burden on enterprises, and enhance corporate vitality—creating a favorable environment for industrial upgrading and transformation. Develop tailored tax policies to support digital and intelligent development, including:

- investment-stage tax incentives such as tax exemptions during project construction and operation;
- production-based benefits including tax deductions and business tax reductions for grid enterprises,
- category-specific policies offering preferential tax treatment for renewable projects by type and development stage,
- carbon pricing tools such as carbon taxes and emissions trading to promote low-carbon transition [10].

Use fiscal subsidies as strategic incentives during different phases of industry development. In the early stages, direct subsidies can effectively stimulate renewable energy deployment. As technology matures and industry competitiveness increases, there will be a gradual shift to market-oriented mechanisms such as competitive bidding, premiums, and contracts for difference [11]. Transition the subsidy focus from generation-side price support to rewarding high-quality service provision by grid enterprises, fostering a competitive and healthy smart grid ecosystem.

3.3.2 Investment and financing policies to enable high-quality industry development

Given the characteristics of energy and power projects—high technical thresholds, large capital requirements, long payback cycles, and stable but modest returns—design robust investment and financing support policies to ensure smooth construction, secure operations, and structural upgrading.

Key measures include:

- Promoting long-term power purchase agreements (PPAs): Enable grid companies to act as buyers in large-scale power purchase models, signing PPAs with renewable generators. These agreements should detail price mechanisms, supply terms, access standards, and certificate requirements, enhancing bankability and facilitating financing.
- Innovating commercial financing models: Encourage diversified societal participation in generation and grid investment. For large-scale projects, adopt

asset securitization and low-interest refinancing; for distributed systems, apply flexible methods such as third-party financing, investment leasing, and secured lending to lower financing barriers.

- Expanding financing channels: Develop inclusive investment models to support broad-based participation in the power sector, fostering new business forms and diversified ownership.
- Green Finance Policies to Promote Sustainable Prosperity of the Power Industry Utilize green finance to support clean energy consumption, energy efficiency, and environmental protection, guiding capital toward advanced technologies and competitive enterprises in low-carbon sectors.

3.3.3 Major policy initiatives

- Building a comprehensive green finance standard system: Refine classification standards for upstream and downstream power sectors, particularly in smart grids, clean energy manufacturing, and system operation.
- Improving green financial instruments: Strengthen green credit and green bond frameworks, and provide targeted support for renewable energy and emerging technology projects.
- Expanding green financial products and markets: Encourage product innovation in electricity, carbon, and green certificate markets. Develop linkages between policy incentives and market functions, and facilitate institutional investor participation (e.g., banks, insurers, securities firms, funds, and export credit agencies).
- Establishing a green finance evaluation and disclosure system: Strengthen information transparency for green power projects, providing financial institutions with the necessary tools and risk assessments to engage safely in green credit, investment, and trading activities. The major policy tools proposed to facilitate electricity markets for smart grids are presented in (Table 1).

Application area	Policy/mechanism examples	Market stage	Regulatory maturity
Electricity Market Design	Multi-timescale trading, spot and long-term integration, and T&D pricing reform	Intermediate to mature	Evolving
Ancillary Services	Inertia services, reactive power pricing, and black-start compensation	Emerging to mature	Developing to advanced
Capacity Adequacy	Strategic reserves, capacity remuneration mechanisms, and scarcity pricing	Early to mature	Varies by region
Cross-border Market Integration	Explicit/implicit auctions, price coupling, and joint market clearing	Intermediate to mature	Regional coordination
Strategic Planning	Integrated source-grid planning and digital transformation roadmaps	Planning phase	Government-led
Financial Mechanisms	Green bonds, PPAs, tax incentives, and carbon pricing	Early to intermediate	Developing

Table 1.
Summary table: Key policies and mechanisms for smart grid enablement.

4. Conclusion

The establishment of an efficient electricity market mechanism and a complete policy guarantee system will effectively promote the construction of smart grids, and the development of power grids also provides a solid physical foundation for market construction. Market construction plans and policy guarantee systems that are conducive to the development of the region should be formulated based on the economic and social conditions, resource endowments, energy and power structures, and other factors of different countries and regions.

Conflict of interest

The authors declare no conflict of interest.

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Section 6

Community-Centric and
Socio-Technical Smart Grid
Applications

Small Productive Processes in Microgrids: Opportunities and Challenges for Sustainable Development of Communities

Danny Espín-Sarzosa, Felipe Valencia, Marcia Montedonico, Carla Lanyon, Jorge Vega and Rodrigo Palma-Behnke

Abstract

Rural production has the challenge of reducing greenhouse gas emissions. This chapter aimed to develop a holistic methodology for such reduction by integrating solar energy by means of rural microgrids (MGs) and small productive processes (SPPs). Socio-technical transitions were taken as a framework to be able to monitor the transitions from the current state toward a stage at which the sustainability of greened rural production can be guaranteed. MGs and SPPs are used, as the former allows solar energy to be harnessed to produce the energy required by rural processes, and the latter enables a technology replacement by solar-energy-based technologies to mitigate greenhouse gas emissions. The deployment of a solar dryer in the Arica region was considered as a test bed. Results showed that the proposed methodology made the technology adoption by the community easy. Integrating MGs with SPPs resulted in better use of solar energy resources available, improved the awareness in the community about solar energy, and improved the decision-making capabilities of the community about energy management. Challenges and learnings from the application of the developed methodology and greening rural production by means of MGs and SPPs are put forward in this chapter.

Keywords: small productive processes, microgrids, rural communities, sustainable development, load modeling

1. Introduction

Integrating renewable energy sources (RES) into rural production has gained relevance due to climate change and the need for green value chains. According to FAO, rural production consumes 30% of global energy and contributes 20% of greenhouse gas emissions [1]. Thus, FAO promotes incorporating modern energy services, including solar energy, for both electricity and thermal applications in rural development strategies [2].

The use of locally available RES, particularly solar energy, has led to the concepts of rural microgrids (MGs) and small productive processes (SPPs). MGs supply energy

to rural production tasks, such as pumping, boiling, or cooling, while SPPs involve production activities using solar energy, including drying, water heating, or photochemical composting (e.g., photofenton) [3, 4]. These systems offer significant potential for greening rural value chains and have been extensively studied for that purpose.

Transforming rural value chains through MGs and SPPs presents several challenges [5], including limited financing and market access for small developers; low adoption of new technologies due to scarce technical capacity; climate-related resource dependency; inadequate infrastructure (electricity, transport, water); and policy or regulatory barriers that hinder the sustainability of small-scale production.

Various strategies have been proposed to address the challenges of integrating SPPs and MGs. As noted in Ref. [6], SPPs support local development and are promoted to boost farm productivity and alleviate poverty. In northern Chile, multiple applications of solar energy in rural value chains have been documented [7]. Technological innovations, such as 3D printing, have also been explored to reduce production waste [8]. Additional examples include ice making, milling, carpentry, egg incubation, water treatment, and camelid fiber processing, all integrating solar energy with complementary technologies [9–12].

This chapter presents a methodology for rural interventions in northern Chile that leverages solar potential to transform value chains through SPPs and MGs [13, 14]. The approach builds on the framework in Refs. [15–17], which identifies innovation niches codeveloped with communities. As these innovations mature, they evolve into socio-technical regimes, fostering new relationships among communities, technologies, and the environment. This progression leads to the socio-technical landscape stage, where transformation sustainability is consolidated.

Beyond socio-technical aspects, the methodology includes a technical evolution involving the development of an energy management system (EMS) that captures the complex behavior of SPPs within rural MGs. The EMS employs voltage-dependent load models, offering improved representation over constant power (CP) models by accounting for voltage impacts at the point of connection. This enhanced modeling strengthens community understanding of MG-SPP interactions, encouraging more efficient use of solar energy by aligning consumption with generation availability.

The methodology was applied to a solar drying process in Chile's Arica region. This chapter presents the integration steps, challenges, and lessons learned, along with the EMS formulation and its simulation using real data. Results showed a $\sim 5\%$ performance improvement over a traditional CP-based EMS. A holistic approach also enhanced technology transfer and community engagement, contributing to more effective adoption of the solar dryer and MG system.

2. Socio-technical systems and participatory methodology

The sustainability of MG interventions depends not only on technological performance but also on community management. Understanding the territory's geographic, cultural, social, and economic context is crucial. Incorporating local perspectives into the innovation process enhances relevance and sustainability. Therefore, a socio-technical systems approach and a participatory, co-construction-based methodology are proposed to guide implementation [18].

2.1 Socio-technical systems

Socio-technical systems represent the interaction between technology, actors, and societal structures [19, 20]. They integrate technical components, organizational decisions, social roles, and practices related to technology use [21]. These systems are shaped by diverse processes, regulations, markets, and cultural meanings across multiple scales [13]. **Figure 1** illustrates the multilevel perspective of such systems.

2.2 Co-construction methodology: Participatory process and technology appropriation

A key challenge in sustaining local development projects is effective technology transfer, which depends on early community involvement and shared decision-making. This is particularly vital in remote areas with high operation and maintenance costs. To support long-term viability and energy transition, a co-construction methodology was developed [13, 14]. This participatory, transdisciplinary approach integrates local and technical knowledge to design energy systems aligned with territorial realities. It emphasizes community participation throughout all stages, promoting ownership and sustainability. Co-construction also addresses challenges such as knowledge asymmetries and differing local perspectives through three foundational pillars.

- Technical and financial viability: Establishing economic and technical conditions that enable projects to function and be sustained over time.

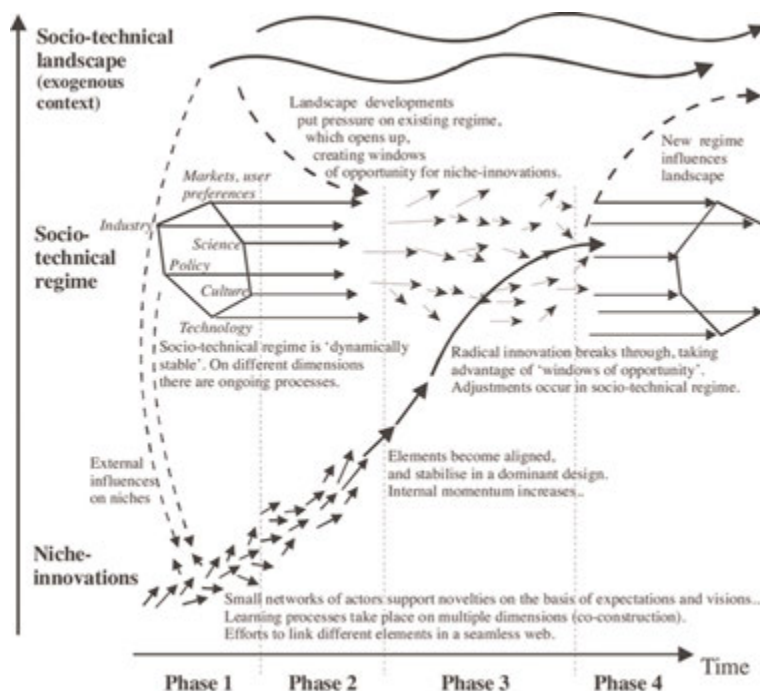


Figure 1.
 Multilevel perspective on socio-technical transitions [15–17].

- Active community involvement: Engaging the community in all stages through informative workshops, discussions, and decision-making processes.
- Education for co-construction: Providing educational workshops to empower individuals with a common foundation and equipping them with useful knowledge for the project's future.

According to Montedonico et al. [14], the co-construction methodology comprises four stages: (1) socio-technical diagnosis and team building, (2) design of the system and sustainability planning, (3) implementation and deployment, and (4) operation, evaluation, and outreach. The methodology pursues a joint learning and participatory design, engaging both technical experts and community members [14]. The structured process, as detailed in Ref. [13] and summarized in **Table 1**, was extracted from Refs. [13, 14], ensures flexibility and alignment with local contexts.

Stage 1, “Socio-technical diagnosis and team building,” focuses on conducting a comprehensive diagnosis to understand community dynamics, daily practices, concerns, and expectations. Key dimensions include governance, productive chains, and land use. Ethnographic and territorial analysis methods are used to address sociocultural challenges. The process begins by identifying local interests and priorities, laying the foundation for aligning the project with territorial realities. According to Montedonico et al. [14], this stage involves several elements.

- Defining flexible technical margins: Identifying elements open to change and those essential for the project's basic requirements.
- Building a transdisciplinary team: Integrating technicians and the local stakeholders (e.g., municipal workers, territorial organization leaders, regional authorities) to serve as counterparts during initial engagement.

Stage	Name	Objectives
Stage 1	Diagnostic and team formation	1.1. Set the technical-structural boundaries (co-construction scope) 1.2. Make diversity visible and identify local leadership 1.3. Share and align on transdisciplinary principles
Stage 2	Socio-technical system design and sustainability plan	2.1. Build participants' capacity for informed decision-making and value local knowledge 2.2. Co-create preferred scenarios 2.3. Jointly specify technical and organizational features 2.4. Draft a sustainability plan with resilience indicators
Stage 3	Implementation and insights	3.1. Implement the project with active community participation 3.2. Capture initial impressions and feedback 3.3. Develop technical and organizational skills for solution management
Stage 4	Operations, assessment, and dissemination	4.1. Conduct follow-up and monitoring 4.2. Assess project performance 4.3. Develop strategies to address weaknesses and gaps 4.4. Disseminate results and lessons learned

Table 1.
Stages of the co-construction methodology adapted from Ref. [14].

- Conducting participatory socio-technical diagnosis: Identifying critical features for project implementation, including social and technical aspects. Preparing an initial energy solution proposal that considers potential future energy transition scenarios.

The second stage, “Socio-technical System Design and Sustainability Plan,” focuses on codesigning a technical solution that integrates local knowledge and aligns with territorial conditions. It includes defining a management model and developing a sustainability plan to ensure long-term viability. Through participatory activities, such as workshops, plenaries, and work sessions, communities build ownership, understand the technology, and contribute to establishing maintenance and business models.

The third stage, “Implementation and First Impression,” focuses on capacity building for system operation and validation of the codesigned solution. It includes three key processes: (i) technology deployment, requiring continuous dialog to address unforeseen issues; (ii) establishment of a legitimate local governance structure to support operation and define roles; and (iii) development of human capital through training in technical and management aspects to ensure community autonomy in system operation and maintenance.

Finally, stage 4, “Operation, Assessment, and Dissemination,” focuses on monitoring, evaluation, and continuous improvement of the socio-technical system. Sustainability indicators guide the development of long-term strategies for energy transition. Dissemination activities, such as solar fairs, workshops, interviews, and evaluation sessions, foster regional linkage and replicability, while codesign processes help address project shortcomings and enhance system performance.

3. Small productive processes and their challenges and learning

3.1 Small productive processes in Chile

As outlined in Section 2, SPP development involves multiple stages influenced by production type, geography, and project scope. Community-focused technological innovations are inherently social projects [22], often implemented through participatory co-construction processes. In Chile, small-scale solar initiatives mainly target residential use, though some promote productive applications. Therefore, SPPs can be defined as small-scale projects that harness solar energy to enhance local productive activities [23]. Their performance depends on external factors such as solar radiation, ambient temperature, wind speed, and relative humidity, among others.

Recently, in Chile, SPP initiatives, supported by the government and universities, have focused on agriculture, aquaculture, and livestock. Common applications include solar-powered irrigation pumps, greenhouses [24], drying systems, solar-assisted shrimp farming [23], and camelid fiber processing [12]. These projects vary in purpose and operational mode, as outlined below.

Solar-powered irrigation water pumping: These projects support water-intensive crop cultivation, improve land use, and promote clean energy adoption [25]. Unlike diesel-based systems, solar irrigation reduces fuel costs, emissions, and maintenance [26, 27]. Key components include photovoltaic (PV) panels, converters, transformers, pumps, batteries, and sprinklers [26]. Further technical details are available in Ref. [28], with Chilean case studies in Ref. [29].

Solar-powered greenhouse: This SPP uses PV systems to supply electricity for lighting and climate control in greenhouses, enhancing crop productivity [30]. Conventional systems rely on fossil fuel generators, which are costly and environmentally unsustainable [31]. Solar energy offers a cleaner, more cost-effective alternative [32]. In Chile, the Foundation for Agrarian Innovation (FIA) has supported several pilot PV greenhouse projects [33].

Solar drying system: Used traditionally for food preservation, solar drying removes moisture to inhibit spoilage and reduce product weight and volume, lowering storage and transport costs [34, 35]. As an SPP, it adds value to local crops and supports community access to new markets. Applications in northern Chilean communities are described in Ref. [23].

River shrimp farming based on solar energy: River shrimp farming (*Cryphiops caementarius*) is a traditional activity in northern Chile, requiring controlled water conditions (temperature, salinity, pH). Given the region's arsenic contamination, solar-powered photochemical treatment is used for arsenic removal [7, 36]. The system also employs water recirculation pumps to regulate temperature. Power consumption varies with ambient temperature and solar radiation, which affect both arsenic removal and thermal regulation.

Camelid fiber collection and processing using solar energy: Camelid fiber processing, a key activity in northern Chile [37], involves ten stages, including scouring with hot water (48–55°C), drying, and spinning. Solar technology enhances this process through PV-powered machinery and solar collectors for water heating. Maintaining fiber quality requires regulating moisture, so variations in humidity affect energy needs for drying. When solar input is insufficient, electric heaters supplement water heating.

Launched in 2017, the Ayllu Solar Project promotes sustainable development in urban and rural communities of Chile's Arica and Parinacota region through the productive use of solar energy [23]. It has supported various small-scale initiatives, including solar-powered agricultural processing, shrimp farming, and camelid fiber processing centers [7, 12], as shown in **Figure 2**.

3.2 Challenges and learning from co-construction processes

Based on the accumulated experience of implementing SPP projects in rural communities [22, 23], it is possible to analyze the main challenges of the intervention process based on four axes, detailed in the following subsections.

3.2.1 Local realities and ways of living

Recognizing and understanding different ways of life enables the co-construction process (between the community and the implementing team) [13, 14]. The community's material living conditions shape a particular everyday life that defines the possibilities for community participation, involvement, and adoption of a technological solution [13]. Observing, understanding, and adapting to the local reality is a premise that facilitates this process. We recommend considering the following aspects related to living conditions and ways of living in the co-construction process:

- *Connectivity:* Limited transportation infrastructure and poor communication networks hinder community engagement and access to external resources, affecting participation in project activities.

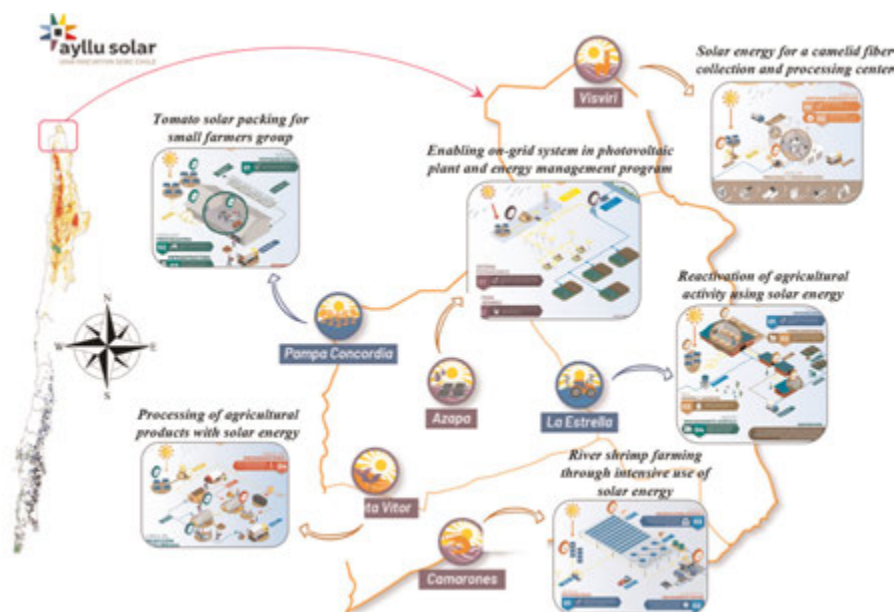


Figure 2.
 Ayllu Solar SPPs located in northern Chile (adapted from Ref. [7]).

- *Access to basic services:* Deficiencies in essential services such as electricity and potable water are typically prioritized by communities, influencing their willingness to participate in initiatives that do not directly address these needs.
- *Livelihoods and productive activities:* Work schedules and subsistence activities limit the time community members can allocate to co-development processes. Therefore, project timelines and engagement strategies must align with local routines and collective meeting practices while minimizing potential economic burdens for participants.
- *Local knowledge and education background:* Disparities in education and local knowledge can reinforce power asymmetries between external technical teams and community members, as well as within the community. These imbalances, particularly evident in communication practices, can obstruct trust-building and inclusive participation.
- *Building capacities:* The complexity of technological solutions must match the community's operational and educational capacity. Training should be context-specific, incorporating culturally relevant, hands-on methodologies that consider age, educational level, and local practices.
- *Community organizational structure:* Social structures, leadership dynamics, and historical experiences shape how communities engage with development projects. Understanding these organizational aspects is vital for identifying legitimate interlocutors and avoiding potential conflicts that may undermine project acceptance and continuity.

- *Funding conflicts:* The community's perception of the funding institution can influence the project's reception. Funding from sources associated with past disputes or conflicting interests may trigger resistance or outright rejection of the initiative.

3.2.2 Internal relation between the developer team

Establishing a shared, interdisciplinary perspective requires ongoing dialog among team members with diverse epistemological approaches to energy transitions. Project governance and inclusive decision-making are key to avoiding biases, such as overemphasizing technical aspects at the expense of organizational or cultural ones. Effective information flow between field teams and project management is essential to adapt to local conditions, refine strategic decisions, and avoid planning errors that may lead to delays, underestimated resource needs, or unfulfilled community expectations.

3.2.3 Relation between the developer team and the communities

Establishing strong relationships and mutual trust between the implementing team and the target community is a critical and complex component of the co-construction process. Key factors influencing trust and motivation include:

- *Stable interlocutors:* Assigning stable representatives from the implementing team enhances credibility and fosters consistent communication. Frequent staff turnover weakens trust, disrupts relational continuity, and forces repeated re-establishment of rapport, delaying project advancement.
- *Regular on-site presence:* Maintaining a regular and meaningful presence within the community strengthens social ties and facilitates contextualized dialog. This physical and symbolic proximity affirms the commitment of the implementation team. However, logistical and geographic challenges must be carefully managed to avoid partial engagement or exclusion of certain community members, which could compromise the perceived legitimacy of decisions.
- *Community motivation:* The design and frequency of participatory activities must be carefully planned. Overloading the community with repetitive or poorly coordinated engagements can diminish interest and lead to high dropout rates. This weakens the decision's legitimacy and may erode the perceived value of the project.
- *Commitment from the developer team:* Delays or unilateral changes to project agreements erode trust and diminish community participation. Respecting collectively made decisions is fundamental to sustaining engagement. Disregarding such agreements risks damaging community relationships and jeopardizing project continuity.

3.2.4 System characteristics

For small productive projects to remain functional and sustainable beyond the co-construction phase, the implemented systems must exhibit technical robustness, economic viability, and organizational maturity. These three interrelated dimensions are outlined below:

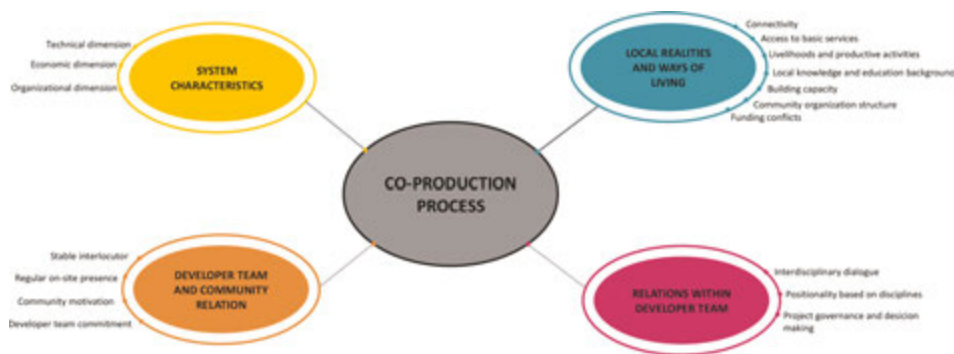


Figure 3.
 Challenges of co-construction.

- *Technical dimension of the technological solution:* The reliability and effectiveness of the technology are central to community acceptance and long-term project success. For initiatives aimed at enhancing local economic activities, proven and accessible technologies are preferable to novel solutions due to their operational reliability, availability of spare parts, and local technical support. It is critical to assess the required skill level for operation and maintenance. Additionally, the selection of the installation site should be consensual to avoid internal conflicts and legal uncertainties, particularly if the land is leased.
- *Economic dimension of the technological solution:* For productive projects, it is necessary to integrate aspects related to the future economic performance of the targeted business into the planning. Due to the associated business risks, marketing training is essential.
- *Organizational dimension of the technological solution:* The ability of the community to autonomously manage the technological solution relies on developing interpersonal and organizational capacities. Soft skills and relationship-building processes are essential components of local governance. Furthermore, establishing alliances with key stakeholders, including government agencies, NGOs, foundations, and private entities, enhances institutional support and integration into broader development programs.

Figure 3 shows the main co-construction process challenges to create energy solutions between the developer team and the community. The challenges are organized in four main themes: system characteristics, developer team and community relations, relations within the developer team, and local realities and ways of living.

4. General aspects related to the modeling of SPP and its integration into EMS for MGs

4.1 Methodology for modeling and integration of SPP into EMS

SPPs exhibit complex behavior due to the diversity and voltage dependence of their electrical loads, which may include devices such as motors, heaters, refrigeration units, and dryers [38]. The interaction of conventional and nonlinear loads increases uncertainty, impacting the reliability, security, and cost-effectiveness of microgrid

operations. To address this, accurate load modeling is essential. The extended multi-zone ZIP (EMZ-ZIP) model, as proposed in Ref. [39] and refined in Ref. [3], is adopted here to represent SPP load behavior within the MG context.

The SPP modeling methodology comprises five stages (A–E) [39]. Stage A involves creating a database of ZIP load models and parameters from field-collected data or available data sources. In Stage B, an EMZ-ZIP model is developed using survey data and observed energy consumption patterns to define consumption zones. Stage C estimates the model parameters through optimization. The EMS is parameterized in stage D by incorporating the EMZ-ZIP model with other loads and distributed energy resources (DERs), considering temporal and spatial load correlations. An AC power flow approach is recommended due to voltage sensitivity. Statistical outputs from this stage support stochastic or robust EMS formulations. Finally, Stage E involves EMS execution.

4.2 Modeling of SPPs in MG context

A widely adopted representation of electric loads is the ZIP model [40]. It expresses demand as a combination of constant impedance (Z), constant current (I), and constant power (P) components. To better capture complex load behavior with this framework, prior studies have introduced piecewise (multistep) or multistage ZIP formulations.

The ZIP model is expressed in Eqs. (1) and (2); the index k ($k \in \mathbb{Z}^+$) represents a discrete time step.

$$P_k = P_0 \left(\alpha_1 \left(\frac{V_k}{V_0} \right)^2 + \alpha_2 \left(\frac{V_k}{V_0} \right) + \alpha_3 \right) \quad (1)$$

$$Q_k = Q_0 \left(\beta_1 \left(\frac{V_k}{V_0} \right)^2 + \beta_2 \left(\frac{V_k}{V_0} \right) + \beta_3 \right) \quad (2)$$

At time step k , the load draws active power P_k and reactive power Q_k . The reference powers at the rated voltage V_0 denotes the measured voltage at k . The coefficient sets $\{\alpha_1, \alpha_2, \alpha_3\}$ and $\{\beta_1, \beta_2, \beta_3\}$, satisfying $\alpha_1 + \alpha_2 + \alpha_3 = 1$ and $\beta_1 + \beta_2 + \beta_3 = 1$, correspond to the active- and reactive power terms, respectively, and quantify the contribution of each feature of the load.

The ZIP model allows flexible parameter specification for each SPP device, using data from experiments, surveys, or existing load model databases [41, 42]. The total SPP load is obtained by summing individual device loads. Eqs. (1) and (2) define the ZIP model, which is extended here to a multi-zone formulation (EMZ-ZIP).

The EMZ-ZIP model extends the standard ZIP formulation by incorporating time-varying behavior to capture load uncertainties and complex SPP characteristics. It defines multiple zones based on distinct load profiles, as illustrated in **Figure 4**. These zones, derived from survey data, remain fixed during EMS implementation.

The EMZ-ZIP model for active power is derived here, and the model for the reactive power is omitted since the same procedure can be applied. One aspect that should be mentioned is that deep learning algorithms can carry out the classification of zones. Specifically, Espín-Sarzosa et al. [39] propose the use of artificial neural networks (ANN) [43] for classification and weather variables as input for the ANN.

Given the above, the EMZ-ZIP model is formulated as follows:

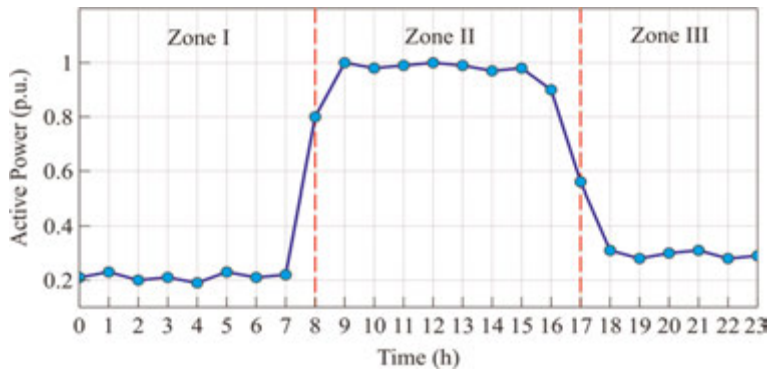


Figure 4.
Illustrative multi-zone of active power.

$$P(k) = ZIP_{flex}(\bar{V}(k)) + \sum_{\omega \in \Omega_{\psi}} \delta_{\omega}(k) ZIP_{\omega}(\bar{V}(k)) \quad (3)$$

$$\sum_{\omega \in \Omega_{\psi}} \delta_{\omega}(k) \leq 1 \quad (4)$$

$$ZIP_{flex}(\bar{V}(k)) = P_{flex}(k) \left(\tilde{\alpha}_1(k) \bar{V}^2(k) + \tilde{\alpha}_2(k) \bar{V}(k) + \tilde{\alpha}_3(k) \right) \quad (5)$$

$$ZIP_{\omega}(\bar{V}(k)) = P_{0,\omega} \left(\alpha_{1,\omega} \bar{V}^2(k) + \alpha_{2,\omega} \bar{V}(k) + \alpha_{3,\omega} \right) \quad (6)$$

Within the EMZ-ZIP framework, $P(k)$ represents the aggregate active demand at instant k . The term $ZIP_{flex}(\bar{V}(k))$ models a flexible share of the load whose ZIP parameters are unknown and must be identified. The weight $\delta_{\omega}(k) \in [0, 1]$ indicates the activation level of device ω (0 when off, 1 when contributing its full power). $P_{flex}(k)$ denotes the rated power at nominal voltage, and $\bar{V}$ is the per-unit voltage. The normalized coefficients $\tilde{\alpha}_1(k)$, $\tilde{\alpha}_2(k)$, and $\tilde{\alpha}_3(k)$ (summing to 1) weight the constant impedance, constant current, and constant power components, respectively. Each zone ψ includes Ω_{ψ} active devices. Using multiple zones removes the need for integer variables, since $ZIP_{\omega}(\bar{V}(k))$ represents each active device per zone with its own identifiable ZIP parameters and associated $\delta_{\omega}(k)$.

4.3 Integration of SPP models into MG

A standard EMS is cast as a mixed-integer linear program that seeks the least-cost microgrid operation across the time horizon K . When network constraints are omitted and only the active power balance is considered, the solution may not ensure power deliverability due to unaccounted reactive power. To address this, a multi-nodal EMS formulation that includes network constraints is adopted, as detailed in Eqs. (7)–(26) [3, 44].

$$\underset{P_g(k), P_b(k), P_{US}(k)}{\text{minimize}} \sum_{k \in K} \left(\sum_{g \in G} C_g P_g(k) + \sum_{b \in B} C_b P_b(k) + C_{US} P_{US}(k) \right) \Delta_k \quad (7)$$

Subject to:

$$\sum_{g \in G} P_g(k) + \sum_{b \in B} P_b(k) + P_{US}(k) = \sum_{n \in N} P_{L,n}(k) + \sum_{s \in B, s \neq r} P_{r,s}^{loss}(k) - \sum_{m \in M} P_{DG,m}(k) \quad (8)$$

$$\sum_{g \in G} Q_g(k) + \sum_{b \in B} Q_b(k) = \sum_{n \in N} Q_{L,n}(k) + \sum_{s \in B, s \neq r} Q_{r,s}^{loss}(k) \quad (9)$$

$$v_g^{min} \leq v_g(k) \leq v_g^{max} \quad (10)$$

$$P_g^{min} \leq P_g(k) \leq P_g^{max} \quad (11)$$

$$P_b(k) = \eta_b^{dis} P_b^{dis}(k) - \frac{P_b^{ch}(k)}{\eta_b^{ch}} \quad (12)$$

$$0 \leq P_b^{ch}(k) \leq P_{b,ch}^{max} \gamma_b^{ch}(k) \quad (13)$$

$$0 \leq P_b^{dis}(k) \leq P_{b,dis}^{max} \gamma_b^{dis}(k) \quad (14)$$

$$\gamma_b^{ch}(k) + \gamma_b^{dis}(k) \leq 1 \quad (15)$$

$$\gamma_b^{ch}(k), \gamma_b^{dis}(k) \in \{0, 1\} \quad (16)$$

$$E_b(k) = E_b(k-1) + \Delta_k \frac{P_b^{ch}(k)}{\eta_b^{ch}} - \Delta_k \eta_b^{dis} P_b^{dis}(k) \quad (17)$$

$$E_b^{init} = E_b^{final}(k) \quad (18)$$

$$E_b^{min} \leq E_b(k) \leq E_b^{max} \quad (19)$$

$$P_{US}(k) \geq 0 \quad (20)$$

$$P_r(k) = \sqrt{2} G_{r,r} u_r(k) + \sum_{s \in B, s \neq r} [G_{r,s} I_{r,s}(k) + B_{r,s} T_{r,s}(k)] + \sum_{s \in B, s \neq r} P_{r,s}^{loss}(k) \quad (21)$$

$$Q_r(k) = -\sqrt{2} B_{r,r} u_r(k) - \sum_{s \in B, s \neq r} [B_{r,s} I_{r,s}(k) - G_{r,s} T_{r,s}(k)] + \sum_{s \in B, s \neq r} Q_{r,s}^{loss}(k) \quad (22)$$

$$l_{r,s}(k) u_r(k) \geq P_{r,s}^2(k) + Q_{r,s}^2(k) \quad (23)$$

$$2u_r(k) u_s(k) \geq I_{r,s}^2(k) + T_{r,s}^2(k) \quad (24)$$

$$\frac{(V_r^{min})^2}{\sqrt{2}} \leq u_r(k) \leq \frac{(V_r^{max})^2}{\sqrt{2}} \quad (25)$$

$$|Y_{r,s}(u_r(k) - u_s(k))| \leq S_{r,s}^{max}(k) \quad (26)$$

Here, Δ_k denotes the length of time slot k . For thermal unit g , C_g is its operating cost and $P_g(k)$ is the active power produced. C_b and $P_b(k)$ represent the battery's cost and power, positive for discharge and negative for charging. $P_{US}(k)$ and C_{US} refer to unserved power and its associated cost. $P_{L,n}(k)$ and $P_{DG,m}(k)$ are the loads at the n -th node and the power from the m -th DG unit, respectively. For each thermal generator g , $v_g(k)$, v_g^{min} , and v_g^{max} define the fuel tank volume constraints, while P_g^{min} and P_g^{max} define power limits.

Over the bus set B , $P_r(k)$, $Q_r(k)$, $V_r(k)$, and $\theta_r(k)$ denote active/reactive power balance, voltage magnitude, and angle at the r -th bus. Eqs. (21) and (22) are convex approximations of the network constraints, based on Ref. [45], enabling efficient EMS integration.

Eq. (17) defines the simplified inter-period energy balance for the battery [44], where $E_b(k)$ is the stored energy. Charging and discharging powers are

denoted by $P_b^{ch}(k)$ and $P_b^{dis}(k)$, with corresponding efficiencies η_b^{ch} and η_b^{dis} . Binary variables.

$y_b^{ch}(k)$ and $y_b^{dis}(k)$ indicate the battery's operation mode, restricted by Eq. (15) to prevent simultaneous charging and discharging. Limits $P_{ch,b}^{max}$, $P_{dis,b}^{max}$, E_b^{min} , and E_b^{max} define operational bounds, while E_b^{init} and $E_b^{final}(k)$ refer to the initial and final stored energy.

The EMS model in Eqs. (7)–(26) does not directly incorporate the EMZ-ZIP model (Eqs. (3)–(6)) due to its non-convex nature. To enable integration, convex approximations are required. Common techniques include Taylor approximation (TAM) and binomial approximation (BAM) [46]. This work applies BAM, as detailed in Ref. [3], to derive a convex form of the EMZ-ZIP model.

$$P_{SPP}(u_r(k)) \approx ZIP_{flex}(u_r(k)) + \sum_{\omega \in \Omega_{\psi}} \delta_{\omega}(k) ZIP_{\omega}(u_r(k)) \quad (27)$$

$$\sum_{\omega \in \Omega_{\psi}} \delta_{\omega}(k) \leq 1 \quad (28)$$

$$ZIP_{flex}(u_r(k)) = P_{flex}(k) \left(\left(\tilde{\alpha}_1(k) + \frac{\tilde{\alpha}_2(k)}{2} \right) u_r(k) + \left(\tilde{\alpha}_3(k) + \frac{\tilde{\alpha}_2(k)}{2} \right) \right) \quad (29)$$

$$ZIP_{\omega}(u_r(k)) = P_{0,\omega} \left(\left(\alpha_{1,\omega} + \frac{\alpha_{2,\omega}}{2} \right) u_r(k) + \left(\alpha_{3,\omega} + \frac{\alpha_{2,\omega}}{2} \right) \right) \quad (30)$$

Eq. (27) and its equivalence of reactive power are added to the EMS formulation. Specifically, Eqs. (8), (9), (21), and (22) are replaced by Eqs. (31)–(34), respectively.

$$\begin{aligned} \sum_{g \in G} P_g(k) + \sum_{b \in B} P_b(k) + P_{US}(k) &= \sum_{n \in N} [P_{L,n}(k) + P_{SPP}(u_r(k))] \\ &+ \sum_{s \in B, s \neq r} P_{r,s}^{loss}(k) - \sum_{m \in M} P_{DG,m}(k) \end{aligned} \quad (31)$$

$$\sum_{g \in G} Q_g(k) + \sum_{b \in B} Q_b(k) = \sum_{n \in N} [Q_{L,n}(k) + Q_{SPP}(u_r(k))] + \sum_{s \in B, s \neq r} Q_{r,s}^{loss}(k) \quad (32)$$

$$P_r(k) - P_{SPP}(u_r(k)) = \sqrt{2} G_{r,r} u_r(k) + \sum_{s \in B, s \neq r} [G_{r,s} I_{r,s}(k) + B_{r,s} T_{r,s}(k)] + \sum_{s \in B, s \neq r} P_{r,s}^{loss}(k) \quad (33)$$

$$Q_r(k) - Q_{SPP}(u_r(k)) = -\sqrt{2} B_{r,r} u_r(k) - \sum_{s \in B, s \neq r} [B_{r,s} I_{r,s}(k) - G_{r,s} T_{r,s}(k)] + \sum_{s \in B, s \neq r} Q_{r,s}^{loss}(k) \quad (34)$$

Finally, the EMS formulation that includes SPP models is given by:

$$\min (7)$$

$$\text{Subject to : (10)–(20), (31)–(34), (23)–(26).}$$

5. Case study and results

The proposed SPP modeling and EMS integration methodology was validated using a 9-bus test system representing a low-voltage MG with a low X/R ratio [47]. This topology reflects typical isolated MGs in Chile, as noted in Refs. [44, 48].

Figure 15 shows the MG, which comprises a pair of diesel generator units (DGU), two

transformers, a photovoltaic (PV) unit interfaced through an inverter, and three load centers. Line parameters and feeder data were taken from Ref. [48].

As depicted in **Figure 5**, the SPP is interfaced at bus 6 and corresponds to a solar-driven dryer for fruits and vegetables. The operation is continuous, and the drying time is mainly governed by ambient temperature and relative humidity [49]. The SPP comprises an electric heater, a ventilation fan, and additional auxiliary loads. Drying is driven primarily by solar irradiance, with electric heating used during low solar availability, and the fan operating under high solar input to control temperature. Auxiliary demands, e.g., lighting and office appliances, operate between 09:00 and 18:00. The electrical usage is metered at the point of interconnection (coupling point).

The first stage (Section 4.1) consists of building a database of ZIP models for devices typically found in SPPs. In the case study, focused on a solar drying facility, device types and their time of use of energy (TOUE) patterns were identified through semi-structured surveys with process operators.

Figure 6 compiles the principal findings of the semi-structured survey of the solar drying operation and components. Based on this, a relational database is created containing ZIP models for each device, with parameters sourced from Ref. [42]. For instance, the heater has $\alpha_{1,heater} = 0.92$, $\alpha_{2,heater} = 0.1$, $\alpha_{3,heater} = -0.02$, and the fan has $\alpha_{1,fan} = 0.26$, $\alpha_{2,fan} = 0.9$, $\alpha_{3,fan} = -0.16$. **Figure 6** also shows the nominal power P_0 of all devices.

The next step involves building the EMZ-ZIP model for the SPP using the ZIP models of devices from **Figure 6**. The process starts with the formulation of the extended time-variant ZIP (TV-ZIP) model for active power, as described in Eqs. (35)–(37) and detailed in Section 4.2. The model's flexible component represents the behavior of auxiliary equipment, which may switch on/off based on user activity.

$$P(k) = ZIP_{flex}(\bar{V}(k)) + \delta_1(k)ZIP_{heater}(\bar{V}(k)) + \delta_2(k)ZIP_{fan}(\bar{V}(k)) \quad (35)$$

$$\delta_1(k) + \delta_2(k) \leq 1 \quad (36)$$

$$ZIP_{flex}(\bar{V}(k)) = P_{flex}(k) \left(\tilde{\alpha}_1(k) \bar{V}^2(k) + \tilde{\alpha}_2(k) \bar{V}(k) + \tilde{\alpha}_3(k) \right) \quad (37)$$

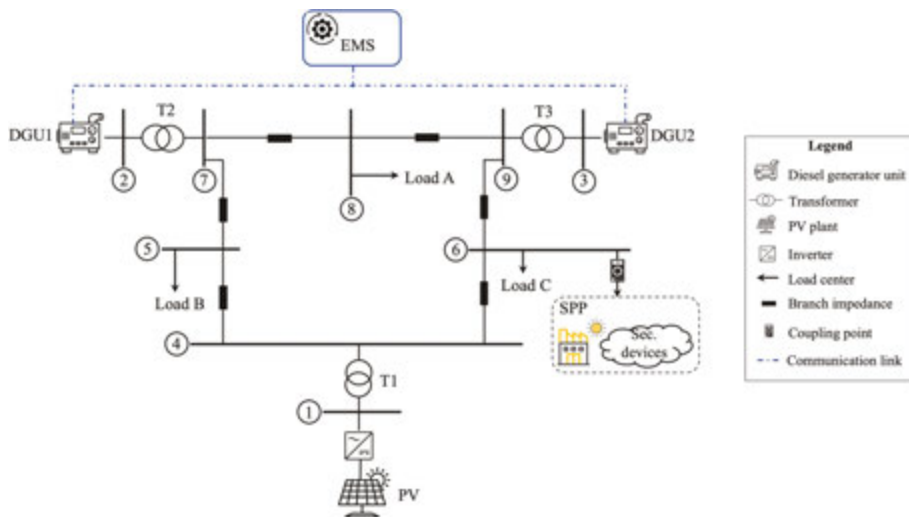


Figure 5.
Overview of the MG for the case study, including the SPP (solar dryer) [3].



Figure 6.
 Results of the semi-structured survey: technical information of the SPP's electrical equipment and their TUE.

Operating zone	Devices in operation	Parameter set to estimate
i	Heater + auxiliary loads	$P_{flex}(k), \tilde{\alpha}_1(k), \tilde{\alpha}_2(k), \tilde{\alpha}_3(k), \delta_1(k)$
ii	Electric fan + auxiliary loads	$P_{flex}(k), \tilde{\alpha}_1(k), \tilde{\alpha}_2(k), \tilde{\alpha}_3(k), \delta_2(k)$
iii	Heater + auxiliary loads	$P_{flex}(k), \tilde{\alpha}_1(k), \tilde{\alpha}_2(k), \tilde{\alpha}_3(k), \delta_1(k)$

Table 2.
 Equipment in service and model parameters to be estimated for each operating zone.

Zoning of the extended TV-ZIP model is performed according to the method in Section 4.2. Inputs for the ANN-based zone identifier include measured solar radiation, temperature, humidity, and time, sourced from Ref. [50]. The training targets are built from time-of-use information gathered in the semi-structured survey (Figure 6).

A multilayer perceptron ANN with sigmoidal activation and Levenberg-Marquardt training is used for zone identification. The input dataset (1296×4) includes 10-minute measurements of solar radiation, temperature, humidity, and time over 54 days. The dataset was partitioned 70%/15%/15% for training, validation, and testing. The trained model is applied to a 48-hour dataset (188 samples), identifying three operating zones (I, II, and III).

According to the timing data from the semi-structured survey (Table 2), the heater operates in zones I and III, the fan in zone III, and auxiliary equipment across all zones. Using Eqs. (35)–(37), a zone-specific extended TV-ZIP model is developed, followed by parameter identification. Figure 6 reports the devices active in each zone and the associated parameter sets.

Parameter identification follows the optimization method in Ref. [3], using 10-minute voltage and power data over a representative day (144 time steps). Input data, simulated from the solar drying process, spans 8 days (1152 samples). Seven days are used for training, and 1 day for validation. Figure 7 displays the estimated active power and the evolution of identified EMZ-ZIP parameters.

To assess model quality, a residual analysis was conducted using the Anderson-Darling normality test [51]. A p -value = 0.07 confirms the residuals follow a normal distribution, indicating the EMZ-ZIP model accurately captures the relationship between SPP power consumption and voltage.

The proposed EMS integration is evaluated through dynamic simulation of the MG. DGU1 manages frequency control, while DGU2 supports voltage regulation when not generating power. The MG operates with 1-ms resolution, and the EMS

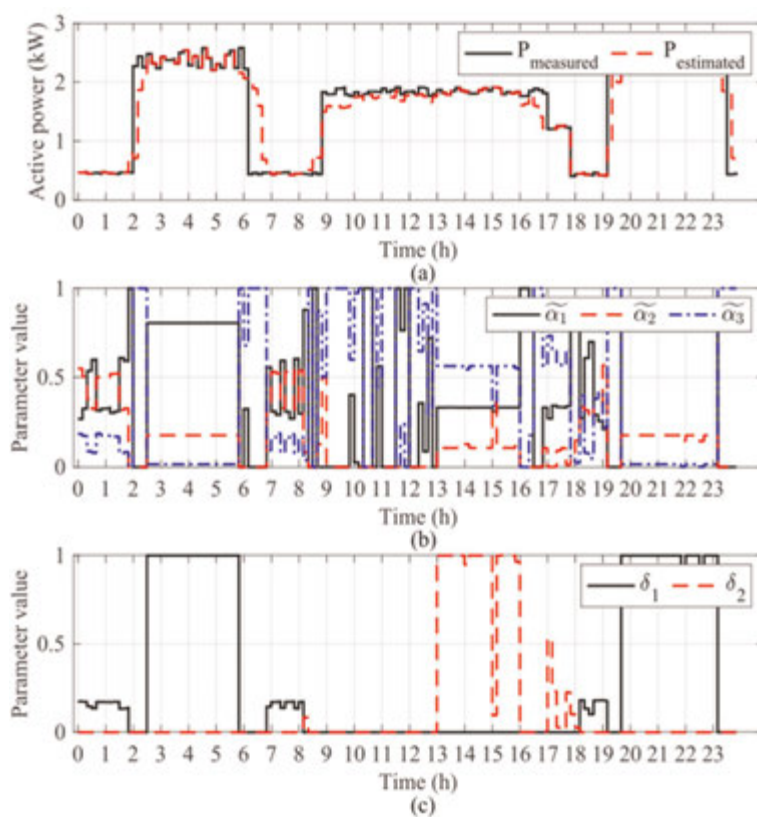


Figure 7.

(a) Comparison between measured and model-estimated active power; (b) trajectories of the identified coefficients $\tilde{\alpha}_1(k)$, $\tilde{\alpha}_2(k)$, $\tilde{\alpha}_3(k)$; and (c) trajectories of the identified activation coefficients $\delta_1(k)$, $\delta_2(k)$.

minimizes operating costs based on generation availability and load forecasts, sending setpoints to dispatchable units every 10 minutes.

A 24-hour analysis was conducted to evaluate EMS performance under three SPP load models: (i) a persistence baseline with constant power (CP) behavior, (ii) a time-varying ZIP formulation (TV-ZIP) [52], and (iii) the EMZ-ZIP approach (Section 4.2). Metrics include actual and expected operating costs (CLP), voltage profiles at generation busses, and SPP power consumption (simulated vs. estimated). All cases use the same PV generation profile. **Figure 8** presents the cost evolution and relative error of the CP model versus the other two approaches.

Figure 8(a) shows that MG operating costs decrease when PV generation is available, mainly from 7:30 to 19:00. In **Figure 8(b)**, the relative error between EMS_{CP} and $\text{EMS}_{\text{EMZ-ZIP}}$ increases after 13:00 due to fan activation. The EMZ-ZIP model, by capturing voltage sensitivity, outperforms the TV-ZIP model in estimating SPP consumption during this period. Additionally, error spikes at 00:00 and 8:00 a.m. are linked to EMS-inactive setpoints at simulation start and to a sharp rise in consumption at the beginning of the work shift.

Tables 3–5 present total and mean operating costs, cost reductions, and relative errors for different SPP load models. **Table 3** shows that voltage-sensitive models reduce total MG operating costs by $\sim 5\%$, as the AC-based EMS lowers load bus voltages to reduce consumption [53]. While the TV-ZIP model shows the highest EMS

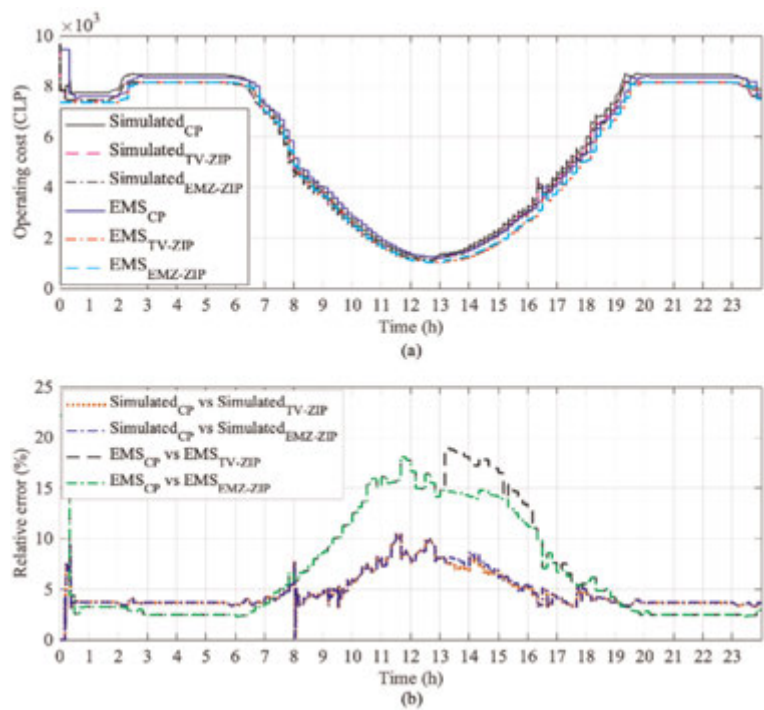


Figure 8.
(a) Comparison of simulated operating costs with EMS cost estimates for the three load models: CP, TV-ZIP, and EMZ-ZIP; (b) Time evolution of the relative cost error of the CP baseline with respect to the TV-ZIP and EMZ-ZIP cases.

Load representation	Total cost (kCLP)	Minimum (kCLP)	Maximum (kCLP)	Mean (kCLP)	Mean reduction (%)
CP	3930	1.23	9.68	5.84	—
TV-ZIP	3770	1.11	9.68	5.61	4.76
EMZ-ZIP	3770	1.11	9.68	5.61	4.80

Table 3.
Statistics of observed MG operating costs.

Load representation	Total cost (kCLP)	Minimum (kCLP)	Maximum (kCLP)	Mean (kCLP)	Mean reduction (%)
CP	3890	1.22	9.45	5.78	—
TV-ZIP	3690	1.04	8.15	5.49	7.45
EMZ-ZIP	3700	1.04	8.15	5.50	7.08

Table 4.
Statistics of MG operating costs estimated by the EMS.

Load representation	Mean (%)	Minimum (%)	Maximum (%)
CP	4.28	2.4×10^{-3}	25.81
TV-ZIP	4.77	5.3×10^{-3}	27.36
EMZ-ZIP	4.36	4.9×10^{-3}	29.36

Table 5. Relative percentage gap between observed MG operating costs and EMS estimates for the three SPP load representations.

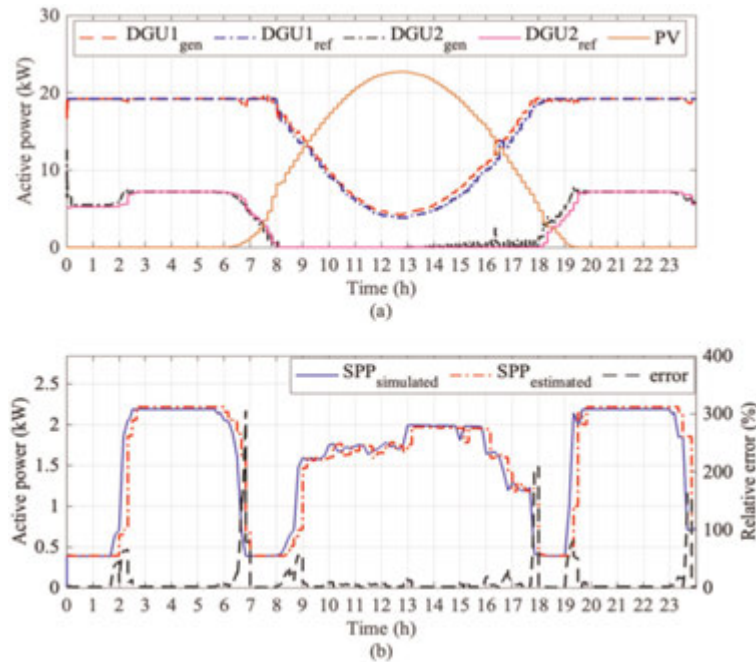


Figure 9. (a) Diesel generator setpoints and measured outputs together with the PV production profile; (b) SPP demand, simulated versus the EMS estimate derived from the EMZ-ZIP model, with the corresponding relative error.

cost reduction in **Table 4**, it overestimates savings due to poor load representation. In contrast, **Table 5** confirms the EMZ-ZIP model yields the lowest error (4.36%) between actual and EMS-estimated costs, reflecting its better accuracy in capturing voltage-dependent behavior.

Figure 9 reports diesel generator setpoints and measured outputs alongside the PV unit's generation trajectory. Panel (b) depicts the SPP load profile produced by the EMZ-ZIP-based simulation and the corresponding relative error with respect to the comparative consumption profile.

As can be seen in **Figure 9(a)**, diesel generators accurately follow EMS power setpoints, reducing output when PV generation increases. As illustrated in **Figure 9(b)**, the EMZ-ZIP model closely estimates SPP consumption, with notable deviations at 7:00, 18:00, and 19:00, corresponding to changes in heater operation and the end of the work shift.

Load representation	Mean (%)	Minimum (%)	Maximum (%)
CP	12.52	1.27×10^{-7}	294.42
TV-ZIP	12.69	1.1×10^{-3}	305.53
EMZ-ZIP	11.97	1.3×10^{-3}	305.26

Table 6.
Relative percentage error between simulated SPP demand and EMS estimates for each load representation.

Table 6 reports the relative discrepancies between the simulated SPP demand and the EMS estimates for the CP, TV-ZIP, and EMZ-ZIP load representations. The summary includes mean, minimum, and maximum errors. Metrics include average, minimum, and maximum errors. The EMZ-ZIP model yields the lowest average error (11.97%), confirming its superior accuracy in capturing voltage-dependent load behavior.

6. Conclusions

Small productive processes are technology-driven solutions aimed at fostering local development. Public agencies and development bodies champion these initiatives as efficient instruments to raise agricultural productivity and reduce poverty. Furthermore, SPPs that integrate RES offer numerous opportunities to environmentally enhance rural value chains, making them a subject of extensive research. However, the transformation of rural value chains through MGs and SPPs faces several challenges, such as (i) limited access to financing and markets for small-scale developers, (ii) limited uptake of technological and operational innovations, stemming from insufficient technical capacity and constrained resources, (iii) the reliance of rural communities on natural resources, which may be vulnerable to climate change, (iv) infrastructure limitations, including restricted access to electricity, transportation, and water supply, and (v) policy and regulatory frameworks that can impede the growth and sustainability of small-scale production. This chapter presented an approach developed for rural interventions in Chile to harness the solar potential of the northern region to transform rural value chains through the deployment of SPP projects and rural MGs. Beyond socio-technical development, the proposed methodology also encompasses the technological evolution required to integrate SPPs into rural MGs effectively. Specifically, an EMS was provided to address the complex behavior of SPPs in the decision-making process, ensuring a balance between energy generation and demand in the rural MG. This EMS employs voltage-dependent load models instead of conventional CP load models, as they better depict the influence of system variables, such as voltage at the connection point, on SPP behavior. The proposed EMS lowered MG operating costs by around 5% relative to a CP baseline. Moreover, adopting a holistic approach facilitated the seamless integration of the solar dryer and MG into the community, with improvements attributed to increased community participation and engagement throughout the process.

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Data availability

Data will be made available on request.

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Smart Grids – Innovations for a Sustainable Future presents a timely and comprehensive exploration of how modern power systems are evolving to meet the demands of decarbonization, digitalization, and resilience. As electricity networks transition toward high shares of renewable energy, inverter-based resources, and data-driven operation, smart grids are emerging as the backbone of a sustainable energy future. This book brings together interdisciplinary perspectives on artificial intelligence in power systems, advanced microgrid control, renewable energy integration, cyber-physical security, electricity markets, and community-oriented energy solutions. It highlights how trustworthy AI, intelligent forecasting, decentralized control, and robust policy frameworks can work together to enhance grid reliability, flexibility, and transparency. By bridging technical innovation with market design and socio-technical considerations, the volume offers a holistic view of smart grid development that goes beyond conventional engineering approaches. Designed for researchers, engineers, policymakers, and advanced students, this book provides valuable insights, conceptual frameworks, and practical perspectives to support informed decision-making and innovation across the smart grid ecosystem, making it a useful reference for those shaping the next generation of sustainable, intelligent power systems.

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