Artificial Intelligence-Driven Management of Sustainable Energy Resources

Visibility, Operation, and Control

Yunyi Li[1] liyunyi@iastate.edu, , Hongyi Li[1] hongyili@iastate.edu, , Wenlong Shi[1] wshi5@iastate.edu, and and Zhaoyu Wang[1] wzy@iastate.edu

[1]Iowa State University, , Ames, , IA , 50010 , USA

Abstract

The rapid global transition toward sustainable energy resources (SERs) is reshaping how modern power systems are observed, optimized, and controlled. While SERs have significantly advanced decarbonization, their weather dependence, variability, and inverter-dominated characteristics challenge traditional, centralized, and deterministic grid operation. At the same time, the proliferation of high-resolution data from inverters, smart meters, and sensors offers unprecedented visibility into system dynamics. Yet, it also exceeds the analytical capability of conventional model-based approaches. Artificial intelligence (AI) provides a new foundation for addressing these challenges by bridging physical laws with data-driven learning, enabling accurate state awareness, adaptive operation, and coordinated control across distributed assets. This article examines how AI transforms the management of SER-rich power systems along three critical dimensions: 1) enhancing visibility by inferring behind-the-meter (BTM) activities, assessing SER flexibility, and reconstructing system states from sparse or noisy measurements; 2) improving operation through AI-enhanced SER service provision, volt/var control (VVC), and dynamic operating envelopes (DOE) for efficiency and security; and 3) advancing control by embedding learning-based intelligence into inverter coordination, voltage and frequency regulation, and long-term dispatch. Together, these developments reveal how AI can convert the variability of SERs from an operational challenge into a source of flexibility, resilience, and intelligence, paving the way toward sustainable, adaptive, and self-optimizing power systems.

Funding

U.S. Department of Energy Office of Energy Efficiency and Renewable Energy,

10.13039/100006134 DEEE0011374

National Science Foundation, 10.13039/100000001 ECCS 2042314

The rapid global transition toward sustainable energy resources (SERs) is reshaping how modern power systems are observed, optimized, and controlled. While SERs have significantly advanced decarbonization, their weather dependence, variability, and inverter-dominated characteristics challenge traditional, centralized, and deterministic grid operation. At the same time, the proliferation of high-resolution data from inverters, smart meters, and sensors offers unprecedented visibility into system dynamics. Yet, it also exceeds the analytical capability of conventional model-based approaches. Artificial intelligence (AI) provides a new foundation for addressing these challenges by bridging physical laws with data-driven learning, enabling accurate state awareness, adaptive operation, and coordinated control across distributed assets. This article examines how AI transforms the management of SER-rich power systems along three critical dimensions: 1) enhancing visibility by inferring behind-the-meter (BTM) activities, assessing SER flexibility, and reconstructing system states from sparse or noisy measurements; 2) improving operation through AI-enhanced SER service provision, volt/var control (VVC), and dynamic operating envelopes (DOE) for efficiency and security; and 3) advancing control by embedding learning-based intelligence into inverter coordination, voltage and frequency regulation, and long-term dispatch. Together, these developments reveal how AI can convert the variability of SERs from an operational challenge into a source of flexibility, resilience, and intelligence, paving the way toward sustainable, adaptive, and self-optimizing power systems.

Introduction

The proliferation of SERs, including solar photovoltaics, wind turbines, energy storage systems, and flexible demand, is transforming the power system landscape. By the end of 2023, SERs supplied roughly 30% of global electricity, with the share expected to approach 46% by 2030 (see IEA 2024 in "For Further Reading"). Their deployment, from utility-level solar farms to rooftop installations and community microgrids, enables cleaner, more efficient, and more resilient energy systems. By decentralizing generation, SERs reduce carbon emissions, mitigate transmission losses, and empower prosumers to contribute to the energy transition actively. Collectively, these advancements bring unprecedented sustainability benefits and lay the foundation for a low-carbon, flexible, and participatory electricity future.

However, the large-scale integration of SERs also introduces technical and operational challenges that strain existing grid architectures. Their weather dependence, variability, and spatial dispersion make traditional deterministic and hierarchical mechanisms increasingly inadequate. These challenges can be summarized as follows:

- *Limited visibility*: SERs are highly dispersed and largely unmonitored, resulting in insufficient observability of real-time injections and voltages. Traditional supervisory control and data acquisition (SCADA) systems sparsely cover distribution feeders, leaving many SERs in a BTM status. The resulting data gaps degrade state estimation, topology inference, and optimal operation, while the rapid fluctuations of SER outputs outpace slow telemetry and advanced metering infrastructure (AMI) reporting intervals.
- *Complicated operation*: The variability and uncertainty of SERs complicate system operation. Rapid changes in irradiance or wind can induce voltage flicker and ramping events, stressing slow-acting voltage regulators. Reverse power flows challenge existing protection coordination and thermal limits. As penetration rises, finding optimal operating points that balance efficiency and reliability becomes increasingly complex and computationally intensive.
- *Intricate control*: Inverter-based SERs reduce system inertia and short-circuit strength, weakening the effectiveness of conventional droop or time-coordinated control. At the primary level, coordinating heterogeneous inverter behaviors is necessary to avoid oscillations; at the secondary level, forecast errors and communication delays can lead to suboptimal setpoints.

These issues demand advanced control paradigms that sustain voltage stability, power quality, and efficiency.

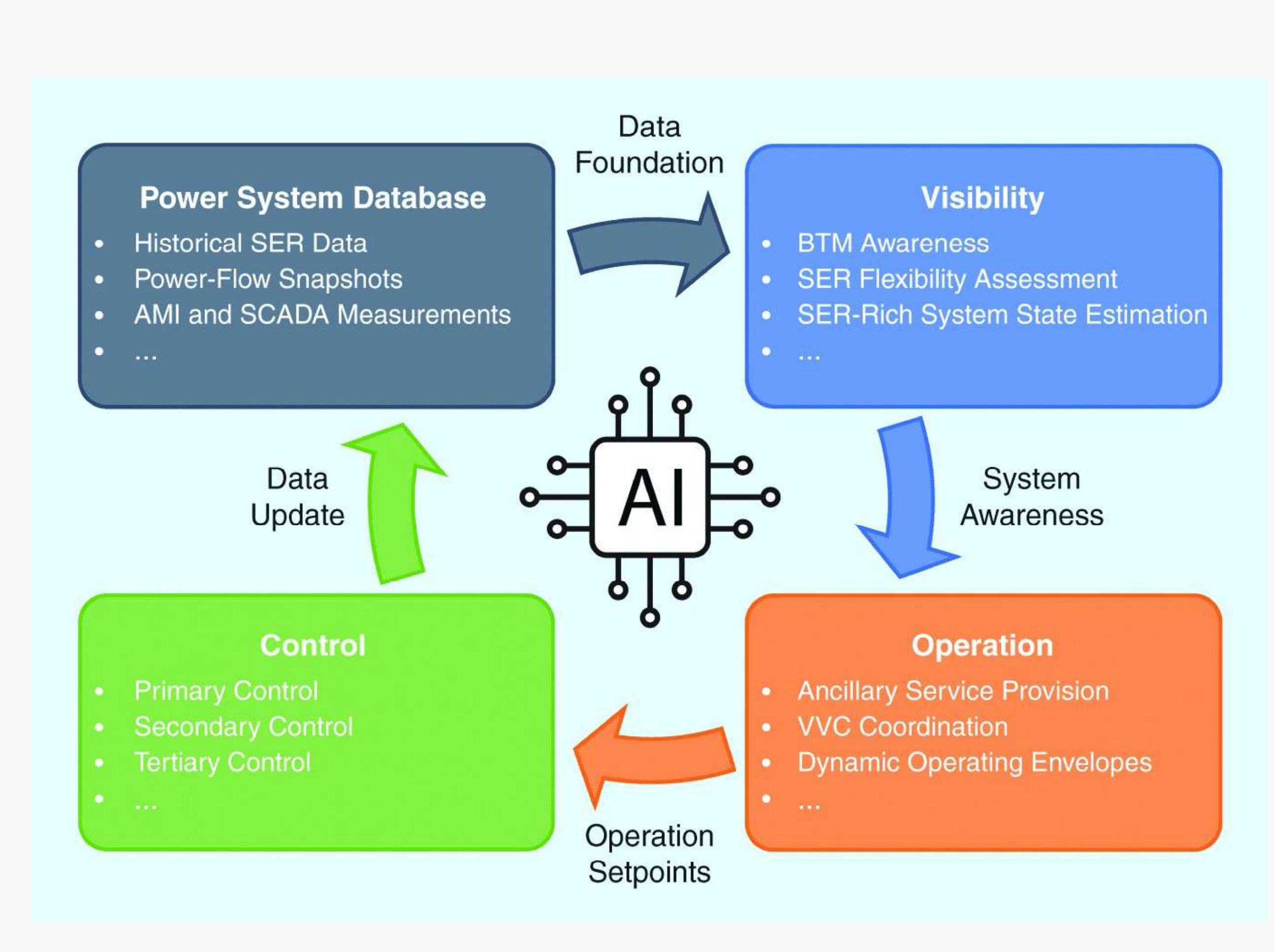
In this complex environment, AI emerges as a transformative enabler. By bridging data and physics and also local behaviors and global objectives, AI provides new means to manage uncertainty, extract hidden knowledge, and orchestrate distributed actions in SER-rich power systems. When properly designed, AI can empower operators to identify BTM contributions, quantify the flexibility of distributed resources, and coordinate multilayer decisions that respect physical constraints while improving economic and environmental performance.

AI introduces three major opportunities that align closely with the core needs of SER integration.

- *Enhanced structural awareness*: AI methods can infer hidden electrical states and SER behaviors from incomplete or noisy data. Graph-based and physics-informed learning embed electrical connectivity into neural architectures, ensuring that learned models remain physically consistent as network conditions or topologies change. This enables accurate and scalable visibility across distributed generation, storage, and flexible demand.
- *Algorithmic acceleration of complex optimization*: The nonlinear and mixed-integer nature of optimization problems in SER-rich systems, such as reactive power coordination, topology reconfiguration, and ancillary service scheduling, can be mitigated through learning-augmented optimization and surrogate modeling. These approaches embed learned representations into optimization solvers, dramatically improving computational efficiency while maintaining engineering feasibility.
- *Adaptive and coordinated control mechanisms*: Reinforcement and hybrid learning frameworks can dynamically tune inverter parameters and coordinate multiple devices to maintain voltage and frequency stability under diverse and uncertain conditions. When combined with graph-based or event-triggered architectures, they enable decentralized yet coherent system-level regulation.

While AI faces challenges related to data robustness, explainability, and generalization, its growing potential still provides a structural solution to revolutionize SER management. In SER-rich power systems, the integration of AI across *visibility*, *operation*, and *control* forms a self-improving loop, as illustrated in Figure 1. Visibility offers the informational foundation, turning dispersed measurements into a coherent understanding of SER flexibility and system state. Based on this awareness, operation identifies decisions that balance reliability, efficiency, and adaptability. Control executes these decisions in real time, stabilizing the system and feeding back updated data for continuous learning. AI interlinks these processes, establishing a complete cycle of perception, optimization, and regulation that continuously enhances the integration and operational reliability of SER-rich power systems.

Figure 1. The overall structure of AI-driven visibility, operation, and control.

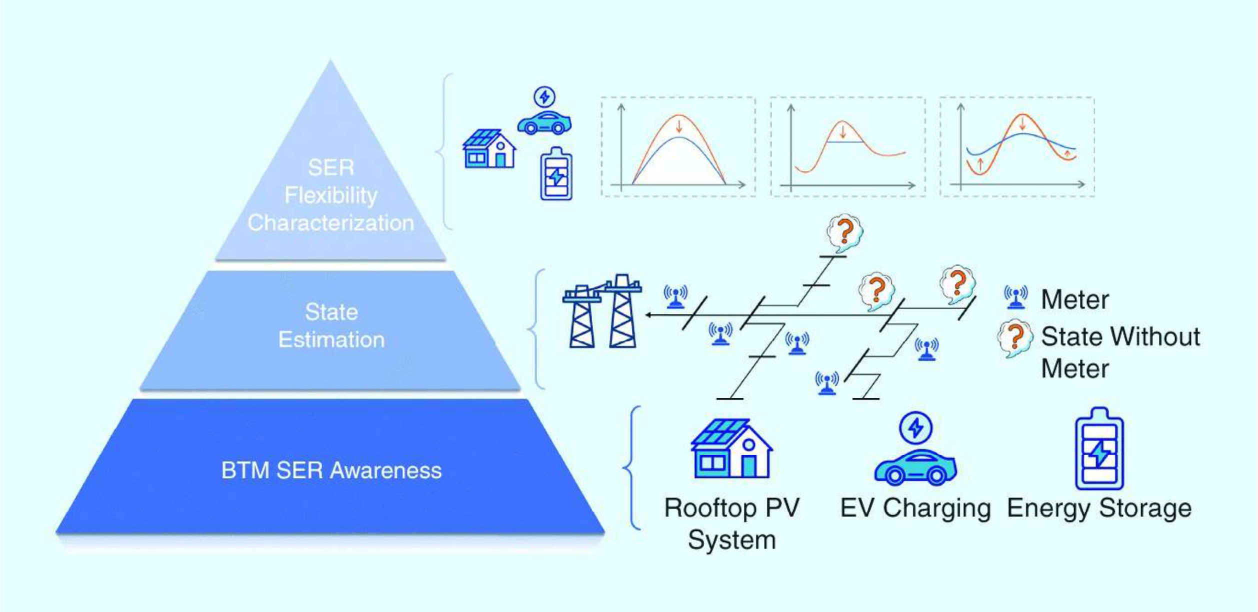


In the remainder of this article, we discuss three major topics related to AI-driven SER management: *visibility*, *operation*, and *control*. For each topic, we introduce the current approaches for specific problems, reveal the motivation of AI-driven solutions, and explore the existing or potential applications of AI methods to facilitate SER integration and utilization. Finally, we conclude this article and discuss future research directions.

Enhancing the Visibility of SER-Rich Systems With AI

Visibility forms the informational foundation of an AI-enabled SER-rich grid. It transforms the scattered, partially observed activities of distributed generation and flexible demand into a coherent, quantifiable understanding of system behavior. In practice, visibility unfolds across three interconnected levels: BTM awareness, system-level state estimation, and SER flexibility assessment, as shown in Figure 2. Together, these layers determine how effectively the grid can perceive itself, anticipate changes, and respond intelligently.

Figure 2. Structure of visibility: BTM SER awareness, state estimation, and flexibility characterization. PV: photovoltaic; EV: electric vehicle.



BTM SER Awareness

BTM resources, including rooftop photovoltaics, residential batteries, electric vehicles, and flexible loads, constitute the least visible yet most active layer of the power system. They respond to weather, user behavior, and local control logic, producing a blend of generation and consumption that utilities cannot directly measure. Traditional disaggregation methods rely on simplified photovoltaic (PV) models, irradiance curves, or static regression between load and temperature. Such models are fragile: once consumption habits or inverter settings change, estimation errors multiply.

AI offers a fundamentally different paradigm by learning nonlinear relationships directly from data. Instead of handcrafting analytical models, neural sequence learners can automatically extract signatures that distinguish solar generation from household demand within aggregated net recordings. Convolutional and recurrent architectures have proven particularly effective. Convolutional layers capture rapid local variations, such as transient shading or voltage fluctuations, while recurrent layers preserve the seasonal dependencies that govern both PV and consumption dynamics. Trained on smart meter and irradiance data, these hybrid models achieve excellent decomposition accuracy across diverse households and weather conditions.

Extending from single meters to feeders, graph-based neural networks incorporate spatial structure and physical connectivity into awareness models. SERs connected to the same feeder share electrical proximity and similar weather exposure. Graph neural networks (GNNs) exploit this by propagating information through the network’s topology, allowing strongly observed nodes to assist unmonitored ones. The result merits improved robustness under sensor loss, topology change, or data latency—conditions that routinely undermine statistical estimators. The incorporation of physical laws within message-passing operations also ensures that inferred PV or load profiles remain physically feasible.

AI-driven awareness now extends beyond SER disaggregation to include latent state estimation. Physics-informed neural networks (PINNs) and autoencoder architectures estimate unmeasured internal states of BTM devices, such as battery state of charge and inverter reactive settings, by embedding current–voltage relationships and operational limits into their learning process. These hybrid physical–data approaches ensure that learned outputs adhere to power-flow constraints, even under sparse data conditions. Deep temporal learning, graph-based inference, and physics-informed modeling transform BTM SERs from unpredictable noise sources into more transparent and quantifiable assets that can be incorporated into higher level operational decisions.

System-Level State Estimation

Once the system can observe what SERs are doing, operators can further obtain a unified view of the power grid’s overall operating condition. State estimation provides a complete description of the

SER-rich power system, including voltages, power flows, currents, and other physical quantities. In transmission systems, dense SCADA and phasor measurement unit **<AU: Kindly check that the expansion of PMU is correct.>** coverage enable accurate estimation, but distribution networks remain sparsely monitored, unbalanced, and dynamically reconfigured. Under these conditions, classical state estimation methods, such as weighted least-squares estimators, may fail to converge or produce unrealistic results.

AI-enhanced state estimation overcomes these limitations by merging topology information, physical constraints, and learned statistical patterns. GNNs model the electrical network directly as a graph, using message passing to infer unmeasured node states from observed neighbors. This topology-aware representation captures both spatial correlation and physical connectivity, ensuring accuracy even with limited sensor data. One notable design, the pruned physics-aware neural network, embeds the topology directly within a sparse neural structure, ensuring that learning follows feasible electrical pathways and improving scalability across large systems.

Another promising line of work combines learning with optimization through differentiable power-flow formulations. A deep statistical solver treats state estimation as a learning–optimization hybrid, integrating Gaussian inference layers and power-flow consistency terms. It provides physically consistent estimates with faster computation than that obtained with iterative solvers and greater robustness under measurement noise. Reinforcement-based architectures further extend these concepts to dynamic environments, adjusting estimation strategies online as the system topology or measurement availability changes.

By embedding domain knowledge within learning architectures, AI achieves a balance between accuracy, interpretability, and scalability. These models can achieve effective state estimates for large, inverter-dominated feeders where conventional techniques are too slow or fragile. As visibility deepens from individual SERs to network states, the self-observing characteristic of the power system provides the essential foundation for operational optimization and stability under high SER penetration.

SER Flexibility Assessment

With the operating conditions of both individual SERs and the power grids, the next challenge is to evaluate what SERs can do, i.e., their available flexibility. Flexibility quantifies the upward and downward adjustment that SERs can provide without violating their operational constraints and the system-level operating constraints. In traditional practice, this capability is estimated by deterministic optimization based on predicted irradiance, load, or state-of-charge trajectories. Such models are computationally intensive, sensitive to forecast errors, and often too conservative, leading to an underutilization of SER potential.

AI brings probabilistic reasoning and adaptivity to flexibility estimation. Instead of fixed margins, data-driven models learn to map local operating conditions to feasible flexibility regions. Neural networks capture nonlinear relationships between irradiance, temperature, and voltage, while deep structures can generalize across resource types and environmental conditions. More importantly, modern approaches represent flexibility as a probability distribution rather than a single deterministic value, quantifying uncertainty in both resource availability and network constraints. The probabilistic results enable operators to balance reliability against opportunity in real time.

A representative direction is probabilistic flexibility-region estimation, in which neural networks approximate the boundary of the feasible real-reactive power space for aggregated SERs. The method samples candidate directions, expands them until device or network constraints are met, and learns the shape of the reachable region through a data-driven surrogate. This technique captures complex nonlinear dependencies and ensures feasibility through embedded chance constraints. These methods, adapted from advances in deep sequence learning for renewable generation prediction, now support the estimation of aggregated resource adjustability.

Emerging developments focus on scalability and transferability. Metalearning allows flexible models trained on one network to adapt to another with minimal retraining, leveraging structural similarities in SER composition. Federated learning offers a privacy-preserving framework in which each local entity trains on its own data while contributing to a shared global model through parameter exchange, rather than sharing raw measurements. Such collaborative architectures are particularly valuable for utilities operating under strict data-sharing constraints. Altogether, these advances elevate flexibility estimation from an offline planning exercise to a dynamic operational capability that evolves with the grid, unlocking the responsive potential of SERs.

AI-Enabled Operation of SERs

As visibility turns distributed behavior into coherent insight, operation must turn that insight into coordinated action. In SER-rich distribution systems, this action will consist of three parts: allowing SERs to behave as service providers, regulating voltage and reactive power in the networks, and adjusting SER outputs with dynamic operating limits. Classical methods, which utilize mixed-integer programming and static topological structures, may struggle as system scale and stochasticity increase. AI helps by learning decision-making relationships that are fast, adaptive, and consistent with physical constraints.

Service Provision From SERs

In modern power systems, SERs are no longer passive producers or consumers of active power. Instead, they can deliver valuable ancillary services by modulating their reactive output or temporarily deviating from the maximum power point tracking (MPPT) point. Through these mechanisms, SERs can provide voltage support, fast frequency response, and congestion relief, and can even contribute to transient stability under certain conditions. The essential question is how to orchestrate these services in real time so as not to sacrifice energy yield or overly violate feeder constraints. Traditional practice often prescribes fixed static margins, i.e., predefined bounds on how far inverters may deviate from MPPT or deliver reactive power, and then optimizes dispatch within those limits. Yet, those static margins tend to be overly conservative (wasting potential flexibility) or excessively aggressive (risking constraint violations). An alternative is to view the problem as a dynamic tradeoff between yield and service, learning from data how much flexibility is safely available under prevailing conditions.

Under this paradigm, data-driven regression models can map local measurements for voltage, power injections, loading, and irradiance onto feasible service margins, enabling each inverter to infer its own safe deviation envelope in real time. Rather than committing to a static margin, each device dynamically estimates how far it can deviate from MPPT while preserving network constraints. Beyond static margin estimation, sequential learning-based controllers, e.g., reinforcement learning

(RL), can actively track the optimal tradeoff over time, adjusting both active and reactive outputs as conditions evolve. A practical architecture often adopts a two-timescale control design, in which slower grid devices (tap changers, on-load tap changers, and capacitor banks) **<AU: Please check whether the preceding edited phrase conveys the intended meaning.>** are scheduled with coarse granularity. At the same time, inverters operate on faster timescales (at the minute or second level) guided by learned policies. In this way, inverters manage fast fluctuations locally, while slower devices provide baseline adjustment.

To scale service provision across many SER units, coordination must incorporate network structure and locality. Graph-aware policies, such as those based on GNNs or attention mechanisms, embed feeder topology and electrical proximity into learned control architectures, enabling each inverter to respond to both its own local state and its neighbors' signals with minimal communication overhead. This approach supports a decentralized or distributed coordination of many inverters, rather than complete centralization. Meanwhile, studies of graph reinforcement learning (GRL) in power systems emphasize how GNN–RL combinations can naturally exploit the grid structure for more scalable decision making (e.g., for voltage control in distribution networks). More recent works also explore safe, multiagent, topology-aware RL strategies. Together, these methods enable SERs to transition from passive injectors to active, coordinated providers of grid support, embedding service provision holistically into their operational logic.

AI-Aided VVC

VVC is the heart of distribution operations: maintaining voltages within limits, minimizing losses, and ensuring good power factors. In SER-rich feeders, VVC expands from a periodic setpoint exercise into a continuous, network-wide technique with nonlinear ac constraints and device couplings. The basic difficulty is comprehensive: the uncertainty of SERs can be challenging to cope with, the approximation may lead to infeasibility, and exact optimization is often NP-hard at realistic scales. AI complements the toolbox in three ways: it learns policies that regulate quickly under uncertainty; it embeds physics and topology, ensuring that decisions remain feasible; and it accelerates inner solves for complex coordination problems.

Numerous studies demonstrate that deep RL can achieve competitive VVC performance while respecting device limitations. A recurring pattern is centralized training with decentralized execution: the P-Q rules are learned offline in a simulator and then deployed to local agents that act based on only local measurements, matching centralized benchmarks while incurring lower communication needs. To protect the network during learning and deployment, model-augmented safe RL utilizes internal predictions of feeder dynamics to verify candidate actions and enforce strict voltage/current bounds. This pattern has been validated in distribution-level volt/var settings.

Policy learning scales further when it considers topological structure. Graph-based multiagent learning uses the feeder graph to inform coordination, where agents share embeddings with nearby nodes, and so their reactive decisions cohere without heavy messaging. Graph-reinforcement approaches for decentralized VVC can reduce voltage violations and losses in large feeders while remaining robust to partial observability. These ideas extend naturally beyond VVC. The same graph-aware abstractions can assist coordination in any nonlinear optimal power-flow (OPF) subproblem that couples many local setpoints through the grid, where end-to-end learning provides fast candidate operations, and a small deterministic correction step ensures feasibility.

Finally, the learning-to-optimize framework compresses expensive inner steps. Instead of solving a full OPF at every time step, a neural surrogate model can produce constraint-aware setpoints that require only a light projection to guarantee the feasibility. In practice, it appears to be a two-layer loop: a trained neural network proposes reactive setpoints, and then a fast check or convex refinement snaps them to the admissible region. This hybrid loop captures most of the nonlinear structure in the learned map while allowing classical solvers to enforce network constraint satisfaction. Evidence across several VVC studies shows that such hybrids reduce the computational burden and smooth real-time operation.

DOEs for SERs

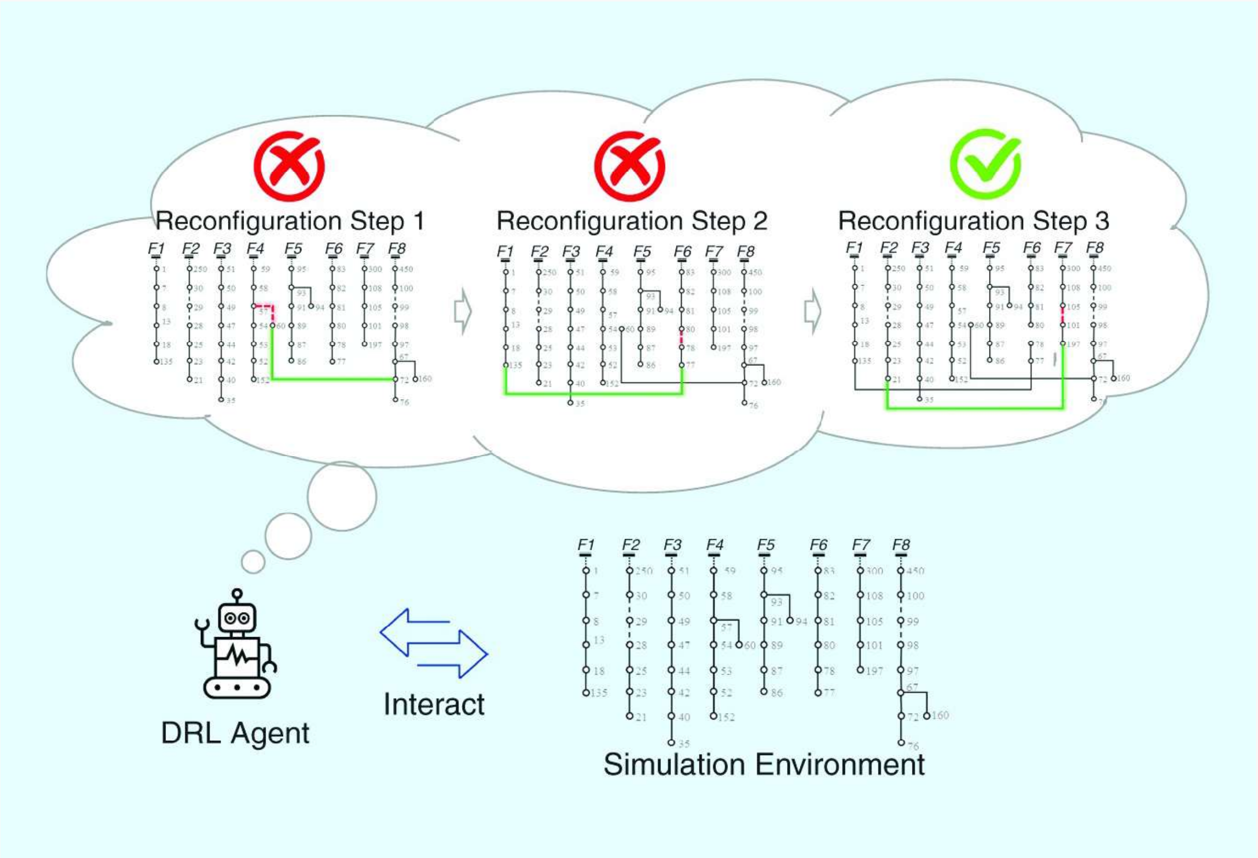
The stochastic, weather-driven, and spatially dispersed nature of SERs introduces frequent power fluctuations, voltage deviations, and bidirectional flows that challenge conventional deterministic operation. Traditional firm interconnection rules, for which SERs are either fully connected or denied access, severely limit the utilization of renewables and prevent the full exploitation of network infrastructure. As penetration levels rise, there is a growing need for dynamic, adaptive mechanisms that can reflect real-time grid conditions and enable SERs to participate safely and efficiently.

The concept of a DOE addresses this need by defining time-varying export and import limits for each SER, capturing local voltage, thermal, and power-flow constraints. DOEs enable SERs to operate flexibly within secure boundaries, achieving a balance between utilization and network operational security. However, existing DOE calculation methods face critical tradeoffs between accuracy and scalability. Model-driven iterative or optimization-based approaches ensure physical consistency but are computationally intensive and unsuitable for frequent updates. Simplified linearized models accelerate computation but may yield conservative or infeasible solutions when actual conditions deviate from assumptions. This tension constrains the operational responsiveness of DOE frameworks, especially under fast SER dynamics and evolving network topologies.

Advances in AI provide a new foundation for efficient and adaptive DOE evaluation. By learning the mapping from nodal injections to state variables directly from data, AI can replace repetitive power-flow solutions with high-speed surrogates. Among these, input convex neural networks maintain convex mapping relationships, enabling DOE optimization to be reformulated as linear programs that can be solved within seconds. Extending this idea, end-to-end learning frameworks integrate model training with optimization objectives, ensuring that neural networks learn decision-relevant features. These approaches transform DOE computation into a real-time, self-correcting process, continuously refining feasible boundaries as conditions change. AI thus bridges data and physics, local behavior and system objectives, enabling SERs to participate actively in system balancing while maintaining operational security.

Beyond optimization, network topology reconfiguration enhances the potential of DOEs by adding structural flexibility to the grid. By changing switch states to redirect power flows, reconfiguration can alleviate congestion, reduce electrical distances, and expand the feasible DOE regions. Coupled with AI, this coordination becomes more powerful. Graph-based learning models capture how network connectivity influences voltage and flow constraints, while deep reinforcement learning (DRL) agents can sequentially learn switch operations that enhance DOE feasibility and SER hosting capacity. In these frameworks, each switching action is treated as a decision step, and system feedback, such as reduced voltage violations or improved loss profiles, guides the agent toward adaptive reconfiguration strategies, as illustrated in Figure 3. The integration of AI-driven DOE optimization with intelligent topology control forms a cohesive, learning-enabled architecture for sustainable distribution systems, allowing them to host high levels of SERs with security, resilience, and economic efficiency.

Figure 3. Interaction between DRL agent and simulation environment in topology reconfiguration. DRL: deep reinforcement learning.



Advanced Control Strategies for SERs

Control is the last barrier in SER-rich systems. Once operators have visibility and operational decisions in place, controllers must intervene on millisecond to hourly scales to stabilize the grid and maintain its reliability. For decades, synchronous machines carried this responsibility, providing inertia and naturally stabilizing dynamics. The rise of inverter-based SERs has eroded this safety framework. Inverters contribute little inertia, their fault currents are low, and their behavior is largely defined by control algorithms.

The consequences are felt across all layers of system operation. Frequency can swing faster after a disturbance, leaving less time to respond. Voltage regulation becomes fragile as distributed PV sources and storage inject or absorb reactive power in unpredictable ways. Protection schemes designed for large fault currents may fail to trigger correctly in low-inertia environments. On top of these physical challenges lies the complexity of scale: thousands or millions of inverters and flexible loads must act coherently, often with only local measurements and limited communication. In this environment, control must evolve from fixed rule sets to intelligent, adaptive strategies that can adjust to uncertainty and scale across devices. AI provides precisely this capacity, complementing classical designs with the flexibility to learn from data and adapt in real time.

AI for Primary Control

Primary control operates in the fastest time frames, reacting almost instantly to disturbances to hold frequency and voltage within acceptable limits. Traditional droop control remains the backbone of primary response, adjusting power output in proportion to frequency or voltage deviations. But droop coefficients fixed at design time are rarely optimal once real-world conditions change. By embedding learning into this framework, controllers can dynamically adjust droop parameters, thereby improving load sharing, and reduce circulating currents. Neural networks and RL agents trained in simulation can efficiently tune these gains, creating controllers that no longer rely on static settings but adapt to evolving grid conditions.

The absence of mechanical inertia may be the most acute challenge. Without the damping influence of spinning masses, frequency deviations can accelerate rapidly. AI-based approaches have been used to emulate inertia by learning how inverters should respond to both the magnitude and the rate of change in frequency. Training on extensive disturbance scenarios allows these controllers to mimic the stabilizing behavior of synchronous machines while tailoring their responses to specific grid contexts. Unlike fixed emulation schemes, they do not deliver the same response every time, but modulate their behavior depending on system conditions. This efficiency gain becomes crucial in heavily renewable grids.

Expanding beyond frequency and voltage stabilization, researchers are exploring controllers that classify disturbances in real time and select context-specific actions. Fast RL strategies can update control strategies as new conditions emerge, while metalearning methods can teach controllers to generalize across various operating environments. With AI-based methods, primary control of SER-rich power systems is evolving from fixed parameter rules into adaptive, context-aware intelligence embedded within each inverter.

AI for Secondary and Tertiary Control

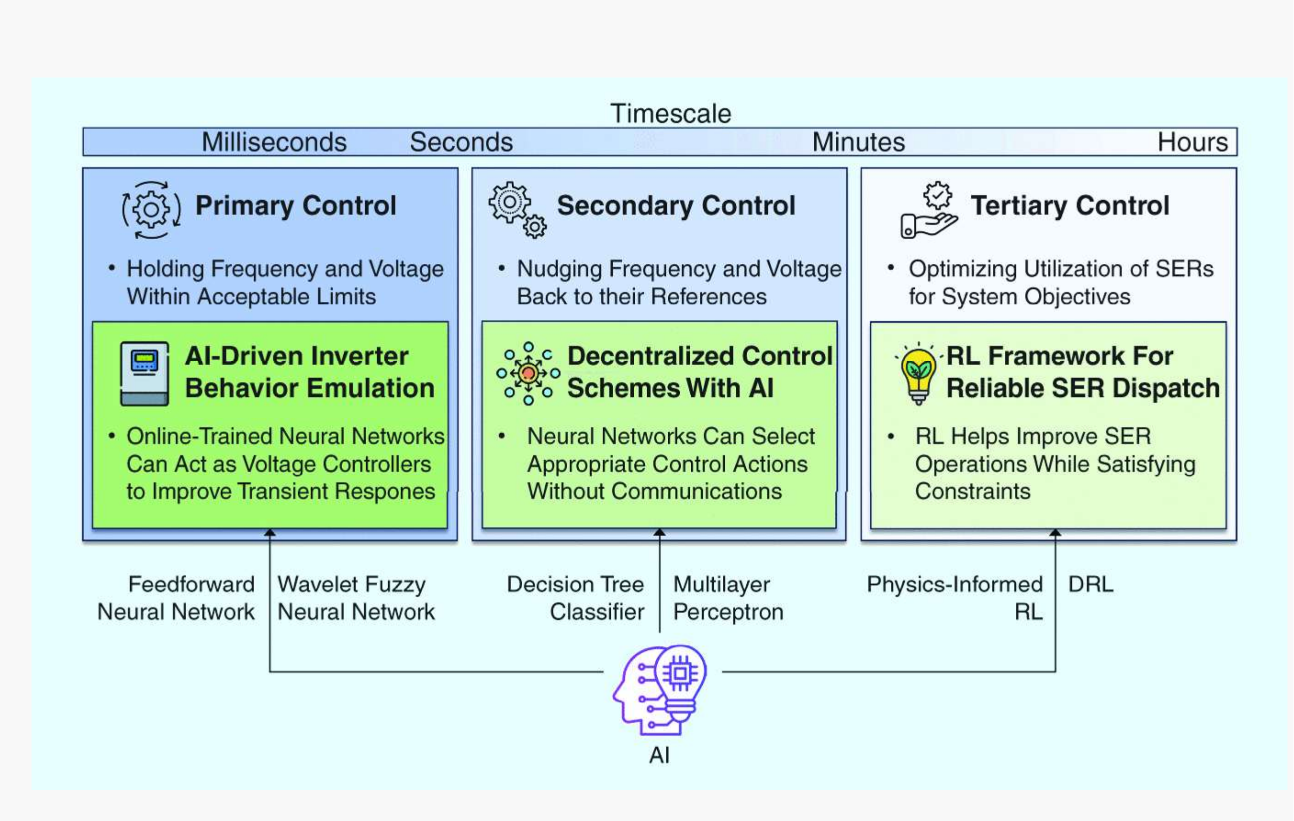
As the immediate disturbance subsides, secondary and tertiary controls take over to restore the system to nominal operation and optimize longer term performance. Secondary control acts over seconds to minutes, nudging frequency and voltage back to their references. Traditionally, this process has been centralized. However, the large number of SER devices in modern distribution networks makes the central mechanism costly and brittle. AI has supported the rise of decentralized coordination, in which each device adjusts its output based on limited communication with neighbors. Consensus-based schemes, augmented with predictive models, enable inverters to anticipate their neighbors' behavior and reduce the need for constant information exchange. This facilitates scalable coordination without compromising performance. Event-triggered strategies further address the communication issues by sharing information only when conditions deviate significantly. AI models help tune these thresholds dynamically, balancing communication efficiency with control accuracy. In practice, this means that devices can operate quietly under stable conditions yet still synchronize effectively when rapid adjustments are needed. Such a framework provides a more resilient communication solution, making decentralized control viable in both dense urban feeders and remote microgrids.

At the tertiary level of SER-rich systems, control expands from stabilization to optimization, where economic, resilience, and sustainability objectives become key considerations. AI contributes by embedding predictive intelligence into scheduling decisions, using probabilistic forecasts of renewables and demand to create dispatch plans that are robust to uncertainty. RL agents trained on long-term system simulations can design storage strategies or flexible demand schedules that minimize costs while enhancing resilience. Hybrid models combine these learning-based policies with traditional OPF solvers, ensuring that economic decisions remain physically feasible. Collectively, these efforts demonstrate how secondary and tertiary controls are being transformed into distributed, predictive, and multiobjective systems that surpass the capabilities of conventional frameworks.

Toward a Comprehensive AI-Aided Framework

AI techniques help formulate a more resilient, adaptive, and efficient framework for controlling SER-integrated power systems. At the primary level, inverters gain agility from neural networks to adapt droop settings, emulate inertia, and classify disturbances in real time. At the secondary level, coordination is made scalable through distributed schemes and adaptive communication. At the tertiary level, RL enriches scheduling decisions, while hybrid solvers preserve the rigor of physical feasibility. Together, these innovations create a control workflow that spans milliseconds to hours, ensuring that SER-rich systems remain stable under stress and optimized under regular operation, which is shown in Figure 4.

Figure 4. AI-driven control hierarchy of SER-rich power systems.



What is most significant is how these layers interconnect with one another. AI provides not only local intelligence but also a unifying thread that allows decisions at one timescale to inform and support others. Visibility informs operation, which in turn provides the context for control, and AI-enabled control closes the loop by stabilizing the grid in real time. In doing so, the variability and uncertainty of SERs, which were once seen as risks, are increasingly transformed into opportunities for flexibility and efficiency. This comprehensive framework signals a path toward grids that are not only sustainable but also intelligent, resilient, and adaptive at every layer of the SER's integration and utilization.

Conclusion

The increasing penetration of SERs brings challenges, including variability, uncertainty, and decentralization, which constrain traditional models of design and operation. However, they also open space for greater flexibility, resilience, and community participation. AI is emerging as a powerful tool to leverage SERs and support the sustainable transition of power systems. The excellent ability of AI to learn from heterogeneous data, recognize complex operational patterns, and adapt strategies in real-time scenarios allows operators not only to manage SER uncertainty but also to treat them as resources. AI creates the foundation for future smart grids to be more sustainable, reliable, and resilient.

This article examines the comprehensive role of AI across three critical fields of SER management. At the level of visibility, AI methods help improve the awareness of BTM SERs, evaluate flexibility, and reconstruct system states, turning incomplete data into comprehensive situational awareness. At the level of operation, AI enables SER-supported service provision, efficient and reliable VVC, and dynamic system reconfiguration. At the level of control, AI empowers inverters and distributed devices to respond rapidly to disturbances, coordinate across scales, and optimize longer term objectives. All of these perspectives highlight how AI extends from high-level planning to real-time stability, embedding intelligence across the full perspectives of SER integration.

Looking forward, the integration of AI and SERs still faces various challenges. Many algorithms still behave as “black boxes,” suffering from uninterpretable decision-making processes and limited trust from system operators. Most models are studied on fixed topologies, ignoring the fact that distribution networks are changing frequently through switching and reconfiguration. The discrepancy between the physical world **<AU: Please check whether the change from “physics world” to “the physical world” conveys the intended meaning.>** and purely data-driven models further raises concerns about the reliability of AI-based SER management models. These issues underscore the need for the next stage of AI–SER integration and call for more trustworthy, adaptive, and resilient approaches. Several promising directions are already emerging.

1. *Topology-aware AI for network-wide SER coordination*: SERs are inherently networked assets, the impacts of which propagate through lines and transformers. Future AI research will increasingly revolve around graph-based intelligence that reasons directly over grid topology. GNNs and GRL can unify decisions on state estimation, VVC, and topology reconfiguration within a single structured framework. Extending these models toward topology-aware decision making will allow SERs across feeders to coordinate autonomously, adjusting their active and

reactive outputs collectively to maintain system-wide stability and efficiency.

2. *Explainable and trustworthy AI for SER operation*: As SERs take on active roles in providing ancillary services and shaping voltages, operators must be able to trust the operation decisions made by AIs. An explainable and transparent decision-making rationale will become a necessity for future AI models, so operators can understand and rely on them. Furthermore, techniques to quantify uncertainty and identify potential errors of AI decisions will become increasingly important, allowing operators to calibrate confidence, implement safeguards, and prioritize human oversight where risk is elevated.
3. *Physics-guided AI for reliable SER integration*: Power systems obey physical laws that must not be overlooked when leveraging AI for visibility, operation, and control. With high SER penetration, pure data-driven AI models could fall short of maintaining the stability of distribution systems. Hybrid frameworks such as PINNs or differentiable power-flow layers will align data-driven results with engineering reality. The combination of physical rigor and adaptive intelligence will define the new paradigm for trustworthy AI in SER-rich grids.
4. *Transferable AI and federated learning for large-scale SER management*: A key obstacle to applying AI for managing SERs is the scarcity of data. Despite substantial differences in network structure, load profile, and SER mix across distribution systems, the core knowledge for SER management is largely transferable, enabling AI deployment in systems with little or even no local data. For example, transfer learning will enable a voltage-control agent trained on one feeder to quickly adapt to another with a different SER configuration. Moreover, federated learning will allow multiple utilities to jointly train AIs across their systems without exposing private or sensitive data. These paradigms will enable regional and even national collaboration in managing SERs while maintaining privacy.

> In SER-rich power systems, the integration of AI across *visibility*, *operation*, and *control* forms a self-improving loop.

> Visibility unfolds across three interconnected levels: BTM

awareness, system-level state estimation, and SER flexibility assessment.

A deep statistical solver treats state estimation as a learning–optimization hybrid, integrating Gaussian inference layers and power-flow consistency terms.

Instead of solving a full OPF at every time step, a neural surrogate model can produce constraint-aware setpoints that require only a light projection to guarantee the feasibility.

Expanding beyond frequency and voltage stabilization, researchers are exploring controllers that classify disturbances in real time and select context-specific actions.

Future AI research will increasingly revolve around graph-based intelligence that reasons directly over grid topology.

Note: this Edit/html view does not display references as per your journal style. There is no need to correct this. The content is correct and it will be converted to your journal style in the published version.

For Further Reading

"Renewables 2024 - Analysis and forecasts to 2030," IEA, Paris, France, Oct. 2024. [Online]. Available: https://www.iea.org/reports/renewables-2024

Z. Wang, B. Chen, J. Wang, M. M. Begovic, and C. Chen, "Coordinated energy management of networked microgrids in distribution systems," IEEE Trans. Smart Grid, vol. 6, no. 1, pp. 45–53, Jan.

2015, doi: 10.1109/TSG.2014.2329846.

M. M. Alam, M. Hossain, M. A. Habib, M. Arafat, and M. Hannan, “Artificial intelligence integrated grid systems: Technologies, potential frameworks, challenges, and research directions,” Renewable Sustainable Energy Rev., vol. 211, Apr. 2025, Art. no. 115251, doi: 10.1016/j.rser.2024.115251.

B. Huang and J. Wang, “Applications of physics-informed neural networks in power systems - A review,” IEEE Trans. Power Syst., vol. 38, no. 1, pp. 572–588, Jan. 2023, doi: 10.1109/TPWRS.2022.3162473.

H. Li, L. Liu, Y. Li, and Z. Wang, “Exploiting convexity of neural networks in dynamic operating envelope optimization for distributed energy resources,” 2025, arXiv:2508.13090.

L. Liu, N. Shi, D. Wang, Z. Ma, Z. Wang, and M. J. Reno, “Voltage calculations in secondary distribution networks via physics-inspired neural network using smart meter data,” IEEE Trans. Smart Grid, vol. 15, no. 5, pp. 5205–5218, Sep. 2024, doi: 10.1109/TSG.2024.3396434.

Acknowledgment

This work was partially supported by the U.S. Department of Energy Office of Energy Efficiency and Renewable Energy under Grant DEEE0011374 and the National Science Foundation under Grant ECCS 2042314.

Yunyi Li (liyunyi@iastate.edu), Hongyi Li (hongyili@iastate.edu), Wenlong Shi (wshi5@iastate.edu), and Zhaoyu Wang (wzy@iastate.edu) are with Iowa State University, Ames, IA 50010 USA. Zhaoyu Wang is the corresponding author.