Intelligent Control of Microgrid System: A Short Review

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Abstract: Microgrids combine distributed generation, storage, flexible loads, and local intelligence into a single operational layer, making it one of the essential building blocks of resilient low-carbon power systems. The control problem they face is inherently multi-time-scale and multi-objective, like converter-level dynamics, which must be stable at the millisecond level; frequency and voltage need to be restored in seconds, but economic dispatch and connection with the grid need minutes to hours for optimization. In this mini-review, authors summarize the latest status and challenges of intelligent microgrid control, where emphasis is placed on adaptive control, model predictive control, distributed and multi-agent control, as well as fuzzy-neural methods and reinforcement learning.

Keywords: intelligent control, model predictive control, adaptive control, multi-agent systems, energy management

1. Introduction

A microgrid can be defined as a localized energy system utilizing distributed energy resources, storage units, controllable loads, and supervisory control to operate grid-connected or in islanded mode. At the technical level, microgrids are green because they improve resilience, host renewable generation, can help reduce network congestion, and enable electrification on campuses, communities, industries, and remote sites. However, these advantages come with rigorous requirements for control. Renewable generation is intermittent, storage devices have state-of-charge limits, loads are partially stochastic, and inertia-dominated networks exhibit fast dynamics. Hence, microgrid control is not a single-loop but a layered decision problem involving converter control, system restoration, economic dispatch, protection coordination, and secure communication [1], [2], [3], [4].

Conventional droop and proportional integral (PI) based control are primary, but the rapid increase of distributed sensing, computation, and data availability brings more research interest in intelligent control. In this review, authors consider intelligent control in its broadest sense as methods that adapt to uncertainty and take advantage of prediction, coordinate distributed agents, or learn from data. That is the adaptive and robust control, model predictive control (MPC), distributed multi-agent coordination, fuzzy-neural control, or reinforcement learning topics [2], [4], [5].

2. Microgrid Architecture and Control Hierarchy

Almost all real-world microgrids are hierarchically structured. Primary control is exercised at the level of the converter (primary level) to achieve stabilization of voltage, frequency, current, and power-sharing within a timescale of milliseconds. Secondary control aims to reinsert the deviations that droop control introduces purposefully, and to schedule voltage or frequency correction over larger time scales. Tertiary control is responsible for power exchange with the utility grid, economic dispatch, demand response, and market participation. Different algorithms fit different layers so that this slightly hierarchical view is still a useful conceptual backbone of intelligent control [1], [2],[4].

Droop control is still a dominant primary strategy for AC microgrids because it enables decentralized power sharing with minimal communication. DC microgrids, on the other hand, also use either current- or voltage-droop implementations. On the other hand, droop control leads to steady-state deviations and performs poorly as line impedance uncertainty, converter heterogeneity, and parameter mismatch grow. Consequently, the secondary control becomes essential to re-establish voltage and frequency, along with effective active and reactive power distribution. Tertiary control optimizes the microgrid even further against external prices, forecasts, emissions, reliability targets, and network constraints [1], [3].

The hierarchy, seen through the lens of intelligence, suggests a design specification in which the faster the loop, the more necessary explicit stability and real-time simplicity are endogenous, while at slower loops, a huge scope exists for prediction, optimization, and data-driven learning. This is why adaptive and robust controllers are particularly suited for primary layers, whereas MPC, distributed optimization, and learning-based policies become more feasible at the secondary and tertiary levels.

3. Intelligent Control Categories for Microgrids

The intelligent microgrid control can be broadly categorized into five categories. The first category consists of adaptive and robust controllers, which update parameters online or shape the closed-loop response against disturbances. These methods are particularly appealing for inverter interfaces because they maintain an intuitive control architecture while enhancing resilience to feeder changes, uncertain inertia, or renewable variability. Adaptive inverter control and frequency regulation techniques developed recently indicate that these schemes can outperform traditional fixed-gain methods in terms of dynamic operating conditions, especially when the PV systems and battery systems are closely coupled [6]. Intelligent control functions for a microgrid in a hierarchical view shows in Figure 1.

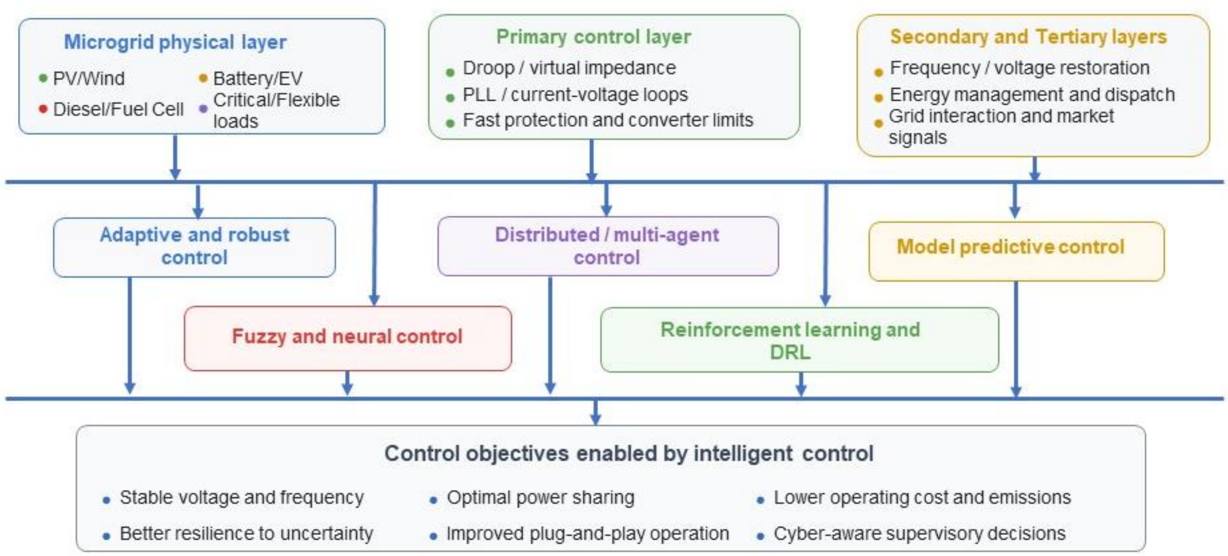

Figure 1. Hierarchical view of intelligent control functions in a microgrid.

The second part of the category will embrace the prediction and constraints handling in microgrid control from MPC and distributed MPC. They can jointly optimize many different variables, such as state-of-charge limits, power balance constraints, converter saturation and ramp-rate limits, in a receding-horizon formulation embedded with economic objectives. As the recent reviews illustrate, MPC has also emerged as one of the most developed intelligent-control approaches for microgrids, particularly with respect to converter control and energy management [7], [8]. The weakness is computational load, mis-specification, and the need for prediction accuracy. Distributed MPC partially solves scaling-up and personal privacy by decomposing the optimization problem on collaborative agents [9].

Third, due to the fact that microgrids are geographically distributed cyber-physical systems, methods for control based on distribution and multi-agent approaches will gain even more importance. Instead of centralization via a controller, agents communicate locally and arrive at consensus on frequency restoration, sharing power, or dispatch. While these methods enhance modularity and plug-and-play capability, they strongly rely on the assumptions of communication reliability, connectivity of the underlying graph, and resilience against malicious or delayed data [4], [10].

Fourth, fuzzy and neural approaches provide nonlinear mapping ability while requiring less computation online. Fuzzy logic provides a means to represent operators' knowledge when finding an accurate model is impossible, and neural approximators characterize nonlinear relationships between the state variables, disturbances, and control actions. These approaches are particularly common in load-frequency control, battery scheduling, and hybrid renewable coordination. It is not only raw performance with them, but their challenge also includes repeatability and stability certification, as well as generalization beyond the training envelope.

Fifth, RL and deep RL deserve much attention because they optimize sequential decisions with uncertainty without exact analytical models. Importantly, recent systematic reviews indicated that RL is being applied to dispatch, voltage regulation, demand response, storage scheduling, and fault-tolerant restoration [11], [12]. For instance, RL is an appealing technique in microgrids when the surroundings are stochastic with high dimensions. But real-world applications remain confined by sample efficiency, exploration safety, cybersecurity risk, and difficulty in establishing rigorous guarantees for stability or constraints satisfaction. Therefore, hybrid-based options like learning policies are enveloped with supervisory safety layers, model-based filters, or also MPC-style constraint shields seem to be the most viable direction [11], [13].

4. Energy Management, Resilience, and Cybersecurity

Intelligent control of microgrid is not only a converter-level issue but rather an energy-management problem. The recent future has challenged energy management systems to decide when to charge or discharge batteries, curtailment of renewable generation, shifting of flexible demand actions with the utility grid, and EV charge support. Subsequently, AI-enabled energy management became a hotspot of research. As AI techniques are trending in forecasting, dispatch, demand response, and resilience improvement at microgrids when EVs and storage are tightly coupled to the microgrid, recent reviews reveal that [5], [14].

A very interesting design challenge is the balance between optimality and interpretability. While deep models might enhance forecast quality or policy performance, operators need transparent decision-making for reliable, risk-compliant operation. This is the reason why a lot of practical architectures set forecasting AI upstream of optimization or rule-based control instead of replacing the entire end-to-end decision chain with an opaque policy. The other big challenge is transferability, i.e., a controller trained on one microgrid topology or climate profile may not work as well on another system. That is, digital twins and domain-adaptation strategies are gradually becoming keys to intelligent energy management.

Intelligent microgrid control links cannot be separated from cybersecurity, since the introduction of communication links, IoT devices, and distributed controllers increases the attack surface. Intelligent control may degrade by false-data injection, denial-of-service, and replay attacks, or compromise a dispatch decision via distributed agents, which in turn can destabilize restoration loops. In a review on cyber resilience in renewable microgrids [10], it was stated that, in the same way control performance is important, secure protocols, anomaly detection, resilient estimation, and standards-based design should also be at the forefront of research. For intelligent controllers, cyber resilience needs to be designed in, not bolted on. In particular, this allows for authenticated data flows, trust-aware state estimation, attack-tolerant distributed coordination, and safe islanded modes.

5. Comparative Analysis

As shown in Figure 2, the comparative analysis of intelligent control methods, no single method outperformed all microgrid layers actually. Adaptive and robust controllers are appealing for fast local loops due to their lightweight and easily certified nature, but have poor performance for long-horizon economic scheduling. MPC shows performed results when strict constraints and forecasts are in place, but efficacy depends on modeling fidelity and optimization resources. Multi-agent methods do scale well for distributed systems and alleviate the issue of sole reliance on a central controller. But they are also vulnerable to communication rate or quality and cyber threats. Fuzzy-neural approaches require moderate computational effort to model complex nonlinearities, while also posing more concerns in terms of tuning and interpretability. RL-based methods are effective for supervisory control in uncertain environments, but they need an aware safety design and reliable training data [4], [5], [6], [7], [8], [9], [11],[12], [13], [14].

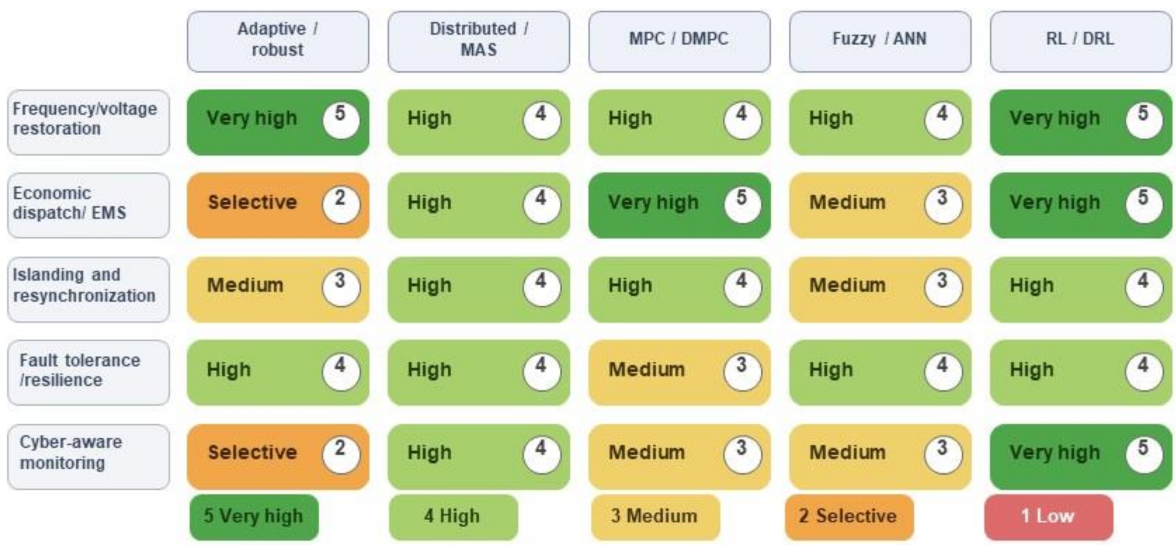

Figure 2. Relative suitability of intelligent control methods across key microgrid tasks.

The strongest trend in the recent literature is convergence rather than competition. Researchers increasingly combine forecasting AI with MPC, distributed consensus with reinforcement learning, or adaptive inner loops with intelligent supervisory layers. In other words, the field is moving toward architecture-level intelligence rather than a single algorithm replacing all others. For practitioners, the design question should therefore be: the level of the hierarchy is being controlled, the critical constraints, the existing communication infrastructure, and the safety requirements. These questions are more useful than the type of algorithm that is globally best. Table 1 shows the comparative analysis of the main intelligent control categories for microgrids.

Table 1. Comparison of major intelligent control categories for microgrids [1]-[14].

Method categories	Typical layer	Main strengths	Key limitations	Data dependence	Best-fit applications
Adaptive/robust	Primary/secondary	Fast response, parameter tolerance, and easier stability analysis	Needs careful tuning; less suited to long-horizon optimization	Low	Inverter control, frequency restoration
MPC/DMPC	Secondary/tertiary	Constraint handling, predictive dispatch, multi-variable optimization	Computational burden, forecast, and model dependence	Medium	EMS, storage scheduling, coordinated converters
Distributed/multi-agent	Secondary/tertiary	Scalable, modular, plug-and-play, privacy-preserving	Sensitive to communication quality and cyber attacks	Medium	Consensus restoration, peer-to-peer coordination
Fuzzy/neural	Primary to tertiary	Handles nonlinear behavior with moderate online cost	Interpretability and certification challenges	Medium to high	Load-frequency control, hybrid renewable coordination
RL/DRL	Secondary/tertiary	Learns sequential decisions under uncertainty; strong for stochastic environments	Safety during exploration, sample efficiency, trustworthiness	High	Dispatch, EV charging, resilience-oriented supervision

6. Future Research Directions

The next phase in intelligent microgrid control is likely to fall into three directions. The first is hybridization. Purely model-free learning remains risky for safety-critical power systems, while purely model-based control struggles with uncertainty and adaptation. Hybrid controllers that fuse state estimation and prediction with responsive, robust fallback logic and learning-based policy improvement are also more applicable in practice.

The second is edge intelligence. Microgrid controllers have been implemented on embedded devices that are close to converters, meters, and protection relays. It means using small models, communication triggered by events, and an inference mechanism stable under latency and packet loss. As such, intelligent control needs to be co-designed with hardware constraints instead of being evaluated solely in cloud-scale simulations.

The third is around standardized benchmarking. One of the biggest challenges in advancing RL and DRL is that many studies differ greatly in modeling, cost functions, cyber assumptions, and measures used to evaluate these frameworks. Joint evaluation of voltage or frequency quality, state-of-charge health, economic cost, resilience, and cyber robustness would create a field that is much more cumulative (see Table 2). Particularly in the case of RL and AI controllers, such benchmarks are critical as reported benefits can vary significantly by scenario [10], [11], [12]. For this purpose, Table 2 shows design guidelines to choose intelligent control methods.

Table 2. Design guidelines for selecting intelligent control methods [10]-[12].

Design requirements	Recommended emphasis	Why	Avoid relying on only
Hard constraint handling and dispatch optimality	MPC/DMPC	Explicitly manages limits, forecasts, and multi-objective costs	Pure droop or untuned heuristic rules
Plug-and-play coordination across many Distributed Energy Sources (DERs)	Distributed/multi-agent control	Improves modularity and reduces central bottlenecks	Single-point centralized logic without redundancy
Fast, certifiable local regulation	Adaptive/robust control	Fits converter-level loops with lower computational burden	Heavy learning models in the innermost loop
Operation under strong uncertainty and complex sequential decisions	RL/DRL with a safety layer	Learns policies for stochastic environments and supervisory actions	Unconstrained model-free learning without safety envelopes

7. Conclusion

Modern microgrids most heavily rely on intelligent controls due to fast local stabilization and slower supervisory intelligence, both required for renewable-rich, inverter-dominated systems. The literature demonstrates that while classical hierarchical control is still the organizing paradigm, intelligent techniques are ever more augmenting each layer. For example, adaptive and robust control enhance converter-level resilience, model predictive control promotes constrained decision making, scalable multi-agent architectures improve scalability through distributed solutions, fuzzy-neural systems produce better representations of nonlinear behavior, and reinforcement learning supervises controls under uncertainty. Replacing classical control is not the most credible path forward, but rather providing model-based guarantees combined with learning-based adaptability. The most effective intelligent control for microgrids will apply algorithms that are not selected simply by what is new, but appropriately mapped to layer, operating constraint, communication context, and safety requirement.

Author Contributions

Both authors reviewed and approved the final version of the paper.

Conflict of Interest

The authors declare no conflicts of interest.

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References

[1] Guerrero, J. M., Vasquez, J. C., Matas, J., De Vicuña, L. G., & Castilla, M. (2010). Hierarchical control of droop-controlled AC and DC microgrids—A general approach toward standardization. *IEEE Transactions on industrial electronics*, *58*(1), 158-172., https://doi.org/10.1109/tie.2010.2066534

[2] Olivares, D. E., Mehrizi-Sani, A., Etemadi, A. H., Cañizares, C. A., Iravani, R., Kazerani, M., ... & Hatziargyriou, N. D. (2014). Trends in microgrid control. *IEEE Transactions on smart grid*, *5*(4), 1905-1919., https://doi.org/10.1109/tsg.2013.2295514

[3] Gao, F., Kang, R., Cao, J., & Yang, T. (2019). Primary and secondary control in DC microgrids: a review. *Journal of Modern Power Systems and Clean Energy*, *7*(2), 227-242. https://doi.org/10.1007/s40565-018-0466-5

[4] Li, S., Oshnoei, A., Blaabjerg, F., & Anvari-Moghaddam, A. (2023). Hierarchical control for microgrids: A survey on classical and machine learning-based methods. *Sustainability*, *15*(11), 8952., https://doi.org/10.3390/su15118952

[5] Khan, M. R., Haider, Z. M., Malik, F. H., Almasoudi, F. M., Alatawi, K. S. S., & Bhutta, M. S. (2024). A comprehensive review of microgrid energy management strategies considering electric vehicles, energy storage systems, and AI techniques. *Processes*, *12*(2), 270., https://doi.org/10.3390/pr12020270

[6] Wang, Q., Li, G., Chen, Z., Jing, Z., & Zhang, Z. (2024). Adaptive control strategy for microgrid inverters based on Narendra model. *Scientific Reports*, *14*(1), 21389., https://doi.org/10.1038/s41598-024-71584-z

[7] Joshal, K. S., & Gupta, N. (2023). Microgrids with model predictive control: A critical review. *Energies*, *16*(13), 4851., https://doi.org/10.3390/en16134851

[8] Razmi, D., Babayomi, O., Davari, A., Rahimi, T., Miao, Y., & Zhang, Z. (2022). Review of model predictive control of distributed energy resources in microgrids. *Symmetry*, *14*(8), 1735., https://doi.org/10.3390/sym14081735

[9] satya nagasri Dangeti, L., & Marimuthu, R. (2025). Distributed model predictive control strategy for microgrid frequency regulation. *Energy Reports*, *13*, 1158-1170., https://doi.org/10.1016/j.egyr.2024.12.071

[10] Rouhani, S. H., Su, C. L., Mobayen, S., Razmjooy, N., & Elsisi, M. (2024). Cyber resilience in renewable microgrids: A review of standards, challenges, and solutions. *Energy*, *309*, 133081., https://doi.org/10.1016/j.energy.2024.133081

[11] Waghmare, A. V., Singh, V. P., Varshney, T., & Sanjeevikumar, P. (2025). A systematic review of reinforcement learning-based control for microgrids: trends, challenges, and emerging algorithms. *Discover Applied Sciences*, *7*(9), 939., https://doi.org/10.1007/s42452-025-07529-6

[12] Dinata, N. F. P., Ramli, M. A. M., Jambak, M. I., Sidik, M. A. B., & Alqahtani, M. M. (2024). Designing an optimal microgrid control system using deep reinforcement learning: A systematic review. *Engineering Science and Technology, an International Journal*, *51*, 101651., https://doi.org/10.1016/j.jestch.2024.101651

[13] Li, F., Tu, W., Zhou, Y., Li, H., Zhou, F., Liu, W., & Hu, C. (2025). Distributed secondary control for DC microgrids using two-stage multi-agent reinforcement learning. *International Journal of Electrical Power & Energy Systems*, *164*, 110335. https://doi.org/10.1016/j.ijepes.2024.110335

[14] Safari, A., Daneshvar, M., & Anvari-Moghaddam, A. (2024). Energy intelligence: A systematic review of artificial intelligence for energy management. *Applied Sciences*, *14*(23), 11112. https://doi.org/10.3390/app142311112