2026 European Conference on Computing in Construction
Corfu, Greece
July 12–15, 2026

A SYSTEMATIC REVIEW OF DISTRIBUTED REINFORCEMENT LEARNING FOR BUILDING-TO-DISTRICT ENERGY NETWORKS

Katharina Steib[1], Thomas Ohlson Timoudas[2], and Qian Wang[1]
[1]Department of Civil and Architectural Engineering, KTH Royal Institute of Technology, Sweden
[2]RISE Research Institutes of Sweden, Kista, Sweden

Abstract

Distributed Reinforcement Learning (RL) enables coordinated HVAC control in district energy systems but existing approaches vary in architecture, addressed challenges, and practical feasibility. This review classifies recent studies by distribution level and problem dimensions and uses a research map to identify trends, research gaps, and future directions for practical, privacy-aware, and safe distributed control.

Framework definition for distribution levels

We introduce a framework that categorizes RL approaches in Building Energy System (BES) by distribution level:

- *L0 Centralized Single-Agent RL* [Zhou et al. (2022), Bao and Xu (2023), Ojand and Dagdougui (2022), Ding et al. (2022)]
- *L1 Partially distributed RL with central Coordination* [Qin et al. (2022), Ahrarinouri et al. (2022), Ruan et al. (2023), Huo et al. (2024), Tomin et al. (2022)]
- *L2 Coordinated distributed RL* [Zhang et al. (2025), Miao et al. (2024), Shen et al. (2022), Bo et al. (2023), Zhu et al. (2024), Tomin et al. (2024), Nweye et al. (2025), Rezazadeh and Bartzoudis (2022)]
- *L3 Fully distributed RL* [Pei et al. (2025), Sun et al. (2024), Zhang et al. (2022b), Tariq et al. (2025), Zhang et al. (2022a)]

Problem categorization

We define system-level core problem dimensions, covering challenges from classical HVAC control, limitations addressed by RL, and new challenges introduced by distributed RL: P1 Scalability, system size and complexity; P2 Coordination and communication; P3 Privacy and Data access; P4 Safety, Stability and Constraint satisfaction; P5 Training efficiency, adaptability and generalization.

Comparison using a research map

Table 1 presents a two-dimensional research map of the 22 reviewed studies, organized by distribution architecture and problem focus. Primary and secondary problems are indicated by filled and unfilled circles, respectively.

With the research matrix we identified the following gaps: 1) limited attention to P3–P5, particularly at higher distribution levels; 2) except for Miao et al. (2024), all reviewed studies rely solely on simulation; 3) few L3 studies and no work addressing all five problems simultaneously.

Table 1: Distribution matrix

	P1	P2	P3	P4	P5
L0				○ ○○○	○ ○○○
L1	○○ ●●○	○ ●●○	○○	○○ ○○○	○○ ●○○
L2	●● ●●● ●●●	●○ ●●● ●●●	○○ ○○○ ●○○	○○ ○○○ ●○○	○○ ○○○ ●○○
L3	●● ●●●	●● ●●●	○○ ●●○	○○ ●○○	○○ ●●○

● primary focus ○ secondary focus

Discussion and conclusion

Rezazadeh and Bartzoudis (2022) combines RL and federated learning for privacy-preserving multi-owner districts. Huo et al. (2024) and Sun et al. (2024) propose safe RL for safety-critical HVAC systems. Ruan et al. (2023) uses offline training on historical data to reduce online exploration.

This work reviewed distributed RL for HVAC control in district energy systems. The key takeaways are: 1) Distributed RL enables scalable and coordinated multi-building control; 2) Major challenges remain: privacy, safety, training efficiency, and real-world deployability; 3) studies address only a subset of problems, highlighting the need for holistic, system-level approaches; 4) Future work should focus on integrated architectures and real-world validation under multi-owner constraints.

Acknowledgements

This study is funded by the Swedish Energy Agency (P2023-01521, TwinVista), and European Union's Horizon Europe programme (101096789, HYSTORE).

References

Ahrarinouri, M., Rastegar, M., Karami, K., and Seifi, A. R. (2022). Distributed reinforcement learning energy management approach in multiple residential energy hubs. Sustainable Energy, Grids and Networks, 32:100795.

Bao, G. and Xu, R. (2023). A Data-Driven Energy Management Strategy Based on Deep Reinforcement Learning for Microgrid Systems. Cognitive Computation, 15(2):739–750.

Bo, W., Wang, X., Jing, G., Xu, H., and Jia, L. (2023). Comfort and energy management of multi-zone

HVAC system based on Multi-Agent Deep Reinforcement Learning. In 2023 IEEE 18th Conference on Industrial Electronics and Applications (ICIEA), pages 1641–1646, Ningbo, China. IEEE.

Ding, Z., Fu, Q., Chen, J., Wu, H., Lu, Y., and Hu, F. (2022). Multi-zone Residential HVAC Control with Satisfying Occupants' Thermal Comfort Requirements and Saving Energy via Reinforcement Learning. In Shen, H., Sang, Y., Zhang, Y., Xiao, N., Arabnia, H. R., Fox, G., Gupta, A., and Malek, M., editors, Parallel and Distributed Computing, Applications and Technologies, volume 13148, pages 441–451. Springer International Publishing, Cham. Series Title: Lecture Notes in Computer Science.

Huo, X., Liu, B., Dong, J., Lian, J., and Liu, M. (2024). Optimal Management of Grid-Interactive Efficient Buildings via Safe Reinforcement Learning. In IECON 2024 - 50th Annual Conference of the IEEE Industrial Electronics Society, pages 1–6, Chicago, IL, USA. IEEE.

Miao, C., Cui, Y., Li, H., and Wu, X. (2024). Efficient multi-agent reinforcement learning HVAC power consumption optimization. Energy Reports, 12:5420–5431.

Nweye, K., Kaspar, K., Buscemi, G., Fonseca, T., Pinto, G., Ghose, D., Duddukuru, S., Pratapa, P., Li, H., Mohammadi, J., Lino Ferreira, L., Hong, T., Ouf, M., Capozzoli, A., and Nagy, Z. (2025). CityLearn v2: energy-flexible, resilient, occupant-centric, and carbon-aware management of grid-interactive communities. Journal of Building Performance Simulation, 18(1):17–38.

Ojand, K. and Dagdougui, H. (2022). Q -Learning-Based Model Predictive Control for Energy Management in Residential Aggregator. IEEE Transactions on Automation Science and Engineering, 19(1):70–81.

Pei, Y., Yao, Y., Zhao, J., Hao, J., Ding, F., and Wang, J. (2025). Multi-Agent Hierarchical Deep Reinforcement Learning for HVAC Control With Flexible DERs. IEEE Transactions on Smart Grid, 16(6):5589–5601.

Qin, Y., Ke, J., Wang, B., and Filaretov, G. F. (2022). Energy optimization for regional buildings based on distributed reinforcement learning. Sustainable Cities and Society, 78:103625.

Rezazadeh, F. and Bartzoudis, N. (2022). A Federated DRL Approach for Smart Micro-Grid Energy Control with Distributed Energy Resources. In 2022 IEEE 27th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks (CAMAD), pages 108–114, Paris, France. IEEE.

Ruan, Y., Liang, Z., Qian, F., Meng, H., and Gao, Y. (2023). Operation strategy optimization of combined cooling, heating, and power systems with energy storage and renewable energy based on deep reinforcement learning. Journal of Building Engineering, 65:105682.

Shen, R., Zhong, S., Wen, X., An, Q., Zheng, R., Li, Y., and Zhao, J. (2022). Multi-agent deep reinforcement learning optimization framework for building energy system with renewable energy. Applied Energy, 312:118724.

Sun, Y., Zhang, S., Liu, M., Zheng, R., and Dong, S. (2024). Energy management based on safe multi-agent reinforcement learning for smart buildings in distribution networks. Energy and Buildings, 318:114410.

Tariq, S., Ali, U., Kim, S., and Yoo, C. (2025). Multi-agent distributed reinforcement learning for energy-efficient thermal comfort control in multi-zone buildings with diverse occupancy patterns. Energy, 332:137082.

Tomin, N., Kolosok, I., Kurbatsky, V., and Korlina, E. (2024). A Demand-Response Approach for HVAC Systems Using Internet of Energy Concept. In Sari, M. and Kulachinskaya, A., editors, Digital Transformation: What are the Smart Cities Today?, volume 846, pages 275–293. Springer Nature Switzerland, Cham. Series Title: Lecture Notes in Networks and Systems.

Tomin, N., Shakirov, V., Kozlov, A., Sidorov, D., Kurbatsky, V., Rehtanz, C., and Lora, E. E. (2022). Design and optimal energy management of community microgrids with flexible renewable energy sources. Renewable Energy, 183:903–921.

Zhang, B., Hu, W., Ghias, A. M., Xu, X., and Chen, Z. (2022a). Multi-agent deep reinforcement learning-based coordination control for grid-aware multi-buildings. Applied Energy, 328:120215.

Zhang, G., Hu, W., Cao, D., Zhang, Z., Huang, Q., Chen, Z., and Blaabjerg, F. (2022b). A multi-agent deep reinforcement learning approach enabled distributed energy management schedule for the coordinate control of multi-energy hub with gas, electricity, and freshwater. Energy Conversion and Management, 255:115340.

Zhang, Y., Zhao, Y., Zhang, C., and Feng, C. (2025). Multi-agent reinforcement learning-based method for demand response of building HVAC systems. Journal of Building Engineering, 108:112734.

Zhou, Y., Ma, Z., Zhang, J., and Zou, S. (2022). Data-driven stochastic energy management of multi energy system using deep reinforcement learning. Energy, 261:125187.

Zhu, S., Lu, W., Feng, Y., and Sun, C. (2024). Energy Optimization for Building Energy Management with Thermal Storage: A Multi-Agent Deep Reinforcement Learning Approach. In 2024 43rd Chinese Control Conference (CCC), pages 2805–2812, Kunming, China. IEEE.