Base station microgrid energy management in 5G networks - a brief review

Yingqi Zhu[1], Kang Li[1], Li Zhang[1]

[1] School of Electronic and Electrical Engineering, University of Leeds, Leeds, LS2 9JT, UK

Abstract. The number of 5G base stations (BSs) constructions has soared in recent years due to the exponential growth in demand for high data rate mobile communication traffic from various intelligent terminals. The 5G BSs powered by microgrids with energy storage and renewable generation can significantly reduce the carbon emissions and operational costs. The base station microgrid energy management system (BSMGEMS) is crucial to unleash these potentials. This paper presents a brief review of BSMGEMS. The work begins by outlining the components and energy consumptions of 5G BSs, introducing the configuration and components of base station microgrids (BSMGs), as well as categorizing the energy management systems (EMSs) and communication network topology. Subsequently, the dispatch optimization strategy and energy trading models are reviewed. The paper finishes with a few suggestions for future research.

Keywords: 5G base stations, energy management systems, energy consumption, scheduling optimization, energy trading.

1 Introduction

The exponential growth of mobile data traffic in a new era of Internet of Things (IoT) has shaped the mass roll-out of the fifth generation (5G) communication technology. At the end of 2023, the global deployment of 5G base stations (BSs) has reached 5.172 million, with China contributing 3.377 million to this total, as reported by the telecommunication development industry alliance (TDIA). The growth is anticipated to continue and the total number of 5G BSs is predicted to rise by 15% in 2025 [1]. The communication networks are energy intensive systems. For example, in 2022, telecommunication networks used 25-30 TWh of electricity in Europe [2]. In cellular network, the BSs consume around 60-80% of the total energy, and even in low traffic period, the BSs consume 90% of their peak energy [3]. Therefore, there is a growing interest to equip BSs with local renewable generators and energy storage (ES) to reduce the carbon footprint and improve energy efficiency, forming a variety of base station microgrids (BSMGs) [4]. However, the energy management systems (EMSs) for 5G BSs have not yet paced with this latest development, and are currently running sub-optimally, facing pressing challenges to integrate energy consumption prediction, scheduling optimization, and energy trading within an integrated framework.

The 5G network is featured with multi-device connectivity, high transmission rates, low end-to-end latency, and high reliability, to meet these requirements. The density of 5G BSs deployment has significantly increased, and the spacing between adjacent BSs has been reduced from the kilometer scale typical of fourth-generation (4G) networks to just hundreds of meters in the 5G era. 5G BSs necessitate greater bandwidth and massive array antennas, resulting in the increase of energy consumption of the 5G network to approximately 2 to 3 times higher than that of the 4G network [5]. The promotion and development of 5G networks greatly depend on the study of the dynamic spatiotemporal distribution of communication loads and energy-saving techniques to guarantee the service quality for the communication loads. Kim et al. proposed an energy-efficient multi-level sleep mode control for periodic transmission (MSC-PUT) in private 5G networks to improve the energy efficiency of BSs [6]. In an effort to achieve an energy-conserving radio access network (RAN), Shen et al. developed a dynamic on-off switching paradigm, where the on and off states of 5G BSs, gNBs can be dynamically configured according to the evolvements of the associated users [7]. These efforts primarily focus on the state control of BSs with the aim to reduce the energy consumption under different traffic load conditions, yet they also entail potential risks, such as compromised communication service quality for operators and poor user experience.

Efficient utilization and intelligent dispatch of ES resources at 5G BSs are crucial for improving energy efficiency, enhancing grid reliability and stability, and facilitating the integration of renewable energy sources (RES). It is shown that when the 5G BS utilizes a dual power supply mode, combining mains electricity and ES backup, the power supply reliability can reach as high as 99%. While the reliability of the BS supply has improved with the energy storage backup, these base station energy storage (BSES) systems often remain dormant for a long period of time, leading to significant wastage of ES resources. Wang et al. introduced Theil's entropy and modified Gini coefficient to quantify the impact of power supply reliability in different regions on BS backup time, thereby establishing a more accurate BS backup ES capacity model [8]. Bao et al. proposed an interesting strategy to safely incorporate gNBs and their ES system into the secondary frequency control procedure to improve power system frequency performance [9]. It is an interesting research topic to aggregate dispersed 5G BSES backup resources and integrate them into the power auxiliary service market in a timely manner to provide frequency modulation and peak shaving services for the power grid, thereby reducing the costs of communication operators. However, it is not an easy task, demanding a comprehensive framework to take into account the load situation, energy consumption and backup ES time to explore the full potential of 5G BSs with energy storage and local renewable energies in providing such services while meeting the quality of services for communication network customers.

Energy trading between 5G BSMGs is another important mechanism to improve the flexibility of the power grid and reduce the carbon emissions of the BSs. A BSMG is an energy-sharing network that combines RES, ES, and various types of BS loads. Yan et al. proposed an energy trading method based on software-defined networking (SDN) and a nonlinear tangent perturbation–multi agent proximal policy optimization (NTP-MAPPO) algorithm to improve the efficiency and renewable energy utilization rate of

BSMGs [10]. Zhou et al. introduced the concept of spatial-temporal energy management (ST-EM) framework, where BSs autonomously manage their electricity consumption based on real-time electricity prices. They also adjust user associations and modify their energy consumption in response to varying electricity prices across different BSs, aiming to minimize the operating costs [11]. Most existing researches focus more on optimizing energy trading for a single 5G BS, efforts on energy trading and distribution among multiple 5G BSMGs are still limited.

This paper presents a brief review of the latest development of BSMGs from four aspects: architecture, energy consumption prediction model, dispatch strategy and energy trading. The main contributions of the paper include: 1) The 5G network topology and energy consumption components are analyzed in depth. 2) The architecture, EMSs and communication network of BSMGs are summarized. 3) The scheduling optimization and ES configuration of the BSMGs are discussed. 4) Various types of energy trading strategies of BSMGs are elaborated. This paper provides a reference for optimizing the energy consumption, operating mode, collaborative dispatching and energy trading of the 5G BSMGEMS to promote the effective utilization of RES.

2 Overview of 5G BSs

2.1 5G substation categorization

5G BSs networks predominantly utilize heterogeneous networks, comprising Macro, Micro, Pico, and Femto. The 5G BSs can be grouped based on their power and capacity. Macro BSs are deployed in regional centers and are responsible for overall network coverage. Low-power BSs are used to supplement the coverage and service quality of Macro BSs. Table 1 summarizes the characteristics of different types of BSs.

Table 1. 5G heterogeneous network BSs parameters [12-14].

Type	Features	Coverage	Transmission power
Macro	Provide broad coverage, connects a large number of users, and has high deployment costs.	1-10km	＞10W
Micro	Complementary Macro BSs, flexible deployment, and low cost.	50-200m	0.5W-10W
Pico	Provide high-density coverage in small areas.	20-50m	0.1W-0.5W
Femto	Use as home BSs.	10-20m	＜0.1W

2.2 5G BSs energy consumption composition

Energy consumption model for 5G BSs is used to predict and manage the energy consumption to support efficient operations and reduce operation and maintenance costs. The energy consumption model for 5G BSs often covers equipment power consumptions under different operation modes, which are then used for optimizing the operation.

Fig. 1 shows the 5G BSs system architecture and Table 2 summarizes the energy consumption model.

Table 2. 5G base station energy consumption model [15-17].

Model	Type	Content
Equipment power consumption	Power supply	AC power supply unit: mains power introduction, mobile oil generator, surge protector, and AC distribution box. DC power supply unit: high-frequency switching combination power supply, and battery.
	Communication	AAU, BBU, radio remote unit (RRU), and network transmission equipment.
	Environment	Lighting, air conditioning and humidifiers.
	Auxiliary	Security and monitoring equipment.
Operating mode	Full power mode	Energy consumption when the BS is fully functional.
	Idle mode	Energy consumption when there is no data transmission.
	Sleep mode	Energy consumption when BS is in low power state.
Optimization technology	Energy efficiency	Dynamic power management and load regulation.
	Energy recovery	Try to recover and reuse some of the energy.
	Energy supply	High-efficiency power conversion equipment and optimized power supply design.

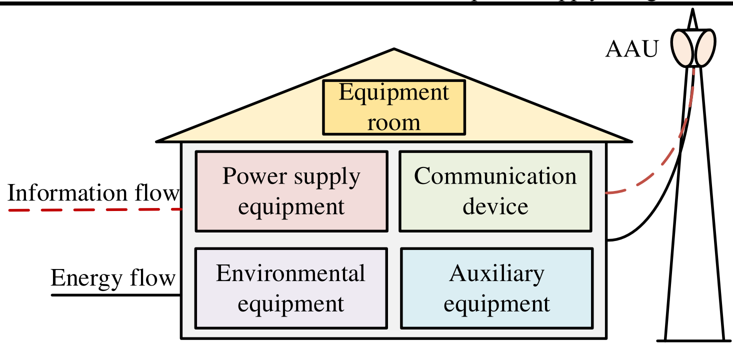

Fig. 1. 5G base station system composition.

3 Introduction to BSMG

3.1 Components of BSMG

BSMG is composed of renewable energy generation units such as photovoltaic (PV) and wind energy, ES equipment, and BS components including air conditioning, baseband units (BBU), active antenna units (AAU), and energy router, as depicted in Fig. 2. Energy supply for BS includes local RES and ES, or can be purchased from other BSMGs. The BSMG energy management center collects information and is responsible for managing the energy flow within the BSMG and energy trading among BSMGs when energy demand and power supply are unbalanced within the BSMG hence at risk of power outages.

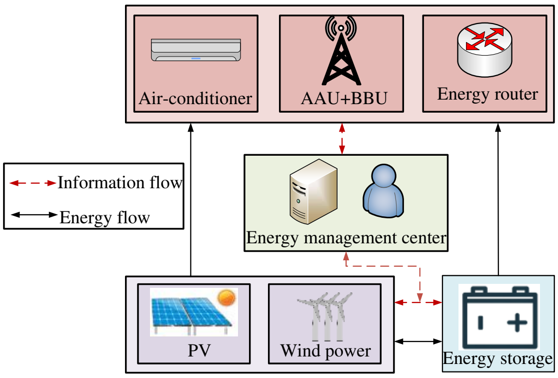

Fig. 2. Main structure of BSMG.

3.2 Configuration of BSMG

Table 3 summarizes the key configuration components of the 5G BSMG in detail, including energy generation, ES, energy conversion, control management system, safety and protection, and network connection. This configuration can help 5G BSs maintain stable services under various environmental conditions while also supporting the use of sustainable energy.

Table 3. 5G BSMG configuration [10, 18-20].

Category	Configuration	Characteristic
Energy generation	Solar panels, wind turbines, and diesel generators	Utilize RES and traditional energy to meet the power needs of the BSs, ensuring diversity and stability of supply.
ES	Lithium-ion batteries and other battery technologies	Store excess electricity for future use, ensuring continuity of power supply and system autonomy.
Energy conversion	Inverters	Convert direct current (DC) to alternating current (AC) to meet the power standards and quality requirements of BSs equipment.
Control and management systems	Microgrid controllers, smart meters, and sensors	Manage and optimize the flow of electricity, achieve efficient energy use, monitor system performance, and conduct fault diagnosis and preventive maintenance.
Safety and protection	Fire protection systems, lightning protection systems, and circuit breakers	Protect equipment and personnel, preventing accidents and malfunctions due to electrical issues or environmental factors.
Network connection	Grid interconnection switches and communication interfaces	Allow the microgrid to connect or disconnect from the main grid and other microgrids, supporting data communication and remote management.

4 BSMGEMS structure, communication and scheduling networks

4.1 BSMGEMS structure

The typical configuration of BSMGEMS is shown in Fig.3 and a comprehensive comparison of these four structures is summarized in Table 4. The configurations of the 5G BSMGEMS include centralized, decentralized, hybrid and nested structure according to its different control and management topology.

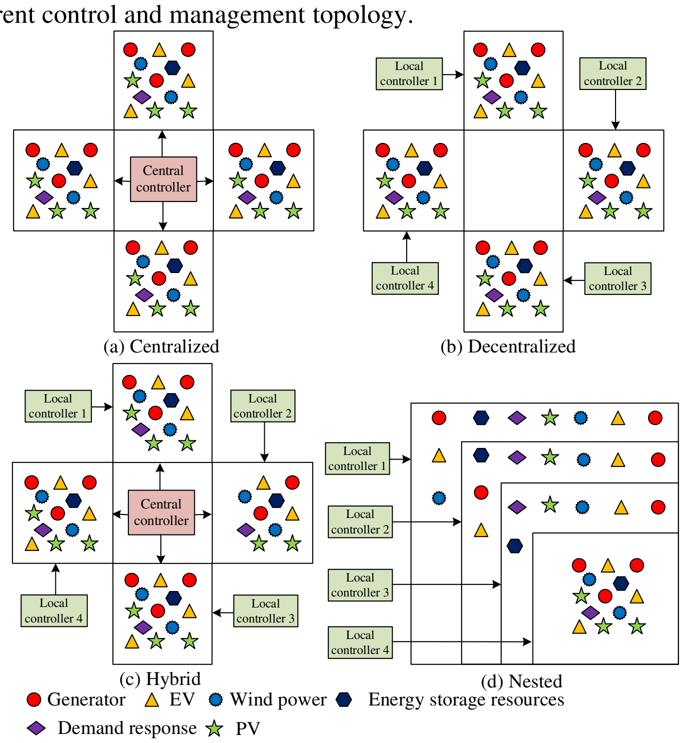

Fig. 3. Typical architecture of BSMGEMS.

Table 4. Characteristics of different BSMGEMS architectures [21-27].

Type	Definition	Strengths	Weaknesses
Centralized	All decision-making and control operations are performed by a central controller.	Easy to monitor and manage. High decision-making consistency. Easy to implement complex optimization algorithms.	There is the single point of failure (SPOF) problem. System is less scalable and flexible.
Decentralized	Management and decision-making are dispersed to multiple	Enhance the system resilience and reliability.	Increase decision-making consistency

	nodes, and each node can independently make decisions and control.	Improve the system flexibility and scalability.	and optimization difficulty. Need more complex communication and coordination mechanisms.
Hybrid	Certain decision-making and control functions are performed by a central controller, while other functions are managed independently by decentralized nodes.	Balance the features of centralization and decentralization. Improve the flexibility and resilience of the system.	System design and implementation are complex. Need to carefully design the distribution of responsibilities.
Nested	Each layer can perform a certain degree of autonomous control, while the upper structure can coordinate and optimize the operation of the lower structure.	Provide high flexibility and scalability. Effectively respond to energy management needs of different scales and complexities.	The control and management structure are complex. Require appropriate hierarchical management strategies.

4.2 Communication network

Fig. 4 illustrates four types of communication networks: Peer-to-Peer (P2P), mesh, aggregation, and nested structures and Table 5 summarizes the key features of these networks. In these diagrams, aggregators function as local controllers for the BSMGs, while the various nodes represent different distributed energy sources and electrical devices equipped with communication capabilities.

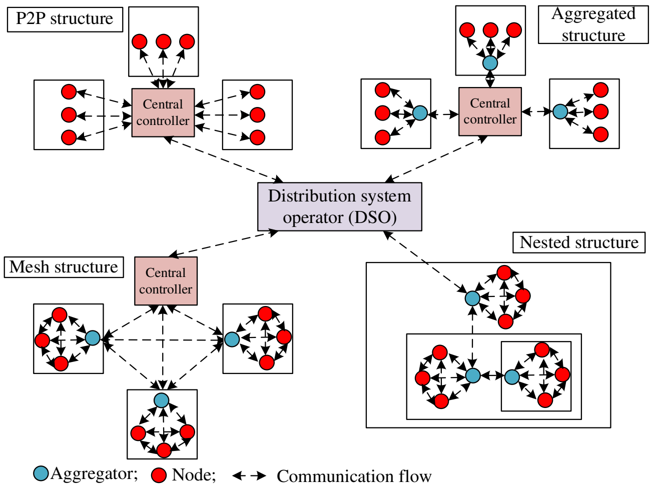

Fig. 4. Typical communication network structure of BSMG.

Among them, the multiple connectivity of the mesh structure is more robust. Even if one connection fails, data can still be transmitted through other paths, ensuring the stable operation of the network. The nested structure adopts a hierarchical approach, where each layer can be independently managed according to requirements while being coordinated and controlled by the upper layer. This structure provides great scalability and flexibility to effectively manage complex systems and diverse energy resources. In short, mesh and nested structures have certain potential in the development of 5G BSMG, but the actual choice of which structure needs to be considered is based on specific network design requirements, cost budget, and technical conditions.

Table 5. Characteristics of different communication network structure of BSMG [28-33].

Type	Definition	Strengths	Weakness	Application
P2P	Each node of the network can communicate directly with other nodes, and there is no central node.	The network structure is simple. Communication between nodes is flexible.	It may lead to increased difficulty in data integration and optimized processing.	It is applicable to the distributed system where nodes need to exchange information directly.
Aggregated	Collect and aggregate information through specific nodes, and then pass the aggregated information to the central node or other nodes.	Reduce the amount of data transmitted to the central node. Efficient data preprocessing.	Longer travel time. There is the SPOF problem.	Suitable for large systems with frequent information exchange.
Mesh	Each node in the network can directly connect and communicate with multiple surrounding nodes to form a mesh structure.	Redundant connections can effectively solve the SPOF problem.	Network management is complex. High running costs.	Ideal for environments requiring high reliability and flexibility.
Nested	Each layer can perform a certain degree of autonomous management, while upper layers can coordinate and manage lower layers.	Effectively protects customer privacy. Lower running costs.	Design and implementation are more complex.	Suitable for systems with large scale, complex structure and requiring hierarchical management and control.

4.3 Scheduling methods

The scheduling optimization of 5G BSs and is a challenging problem. The base station load and capacity are dependent on various factors such as user distribution, communication intensity, and power supply reliability in the area where the BS is located. 5G BSES is different from conventional ES and requires sufficient backup capacity to ensure the reliability of BS power supply. Table 6 summarizes the characteristics of three types of scheduling approaches, including artificial intelligence (AI) method, conventional method and metaheuristics algorithm.

Table 6. Comparisons of different scheduling strategies.

Type	Strategy	Strengths	Weakness	Application
AI method	Fuzzy logic [34]	Flexible handling of imprecise or uncertain information. Low system complexity.	Not as accurate and stable as other advanced algorithms.	Deal with ambiguous and uncertain environments.
	Game theory [35]	Effectively handle decision-making issues involving multiple parties.	Require complex strategy design and equilibrium analysis. High computational cost.	Competitive or multi-user environments.
	Multi-agent [36]	Emphasize system autonomy and collaboration.	Complex design and debugging requires efficient communication protocols.	Distributed resource management and multi-source energy system coordination
	Neural network [37]	Able to process large amounts of data.	High requirements on data quality and quantity. Training process may be time-consuming.	Demand forecasting and complex system behavior modeling
	Reinforcement learning [38]	Self-learning and optimization by interacting with the environment.	Encounter convergence issues.	Dynamically changing environments, such as adapting to market changes.
	Swarm intelligent [39]	Better scalability and robustness.	Algorithm parameter adjustment is complex.	Distributed EMS with diverse needs and large time changes
Conventional method	Bi-level programming [40]	Handle leadership-subordinate multi-level decision-making problems with a clear structure.	The model is complex and difficult to solve.	EMS with a clear hierarchy of decision makers
	Dynamic programming [41]	Handle multi-stage decision-making problems.	The curse of dimensionality problem.	Sequential decision-making problems
	Mixed integer programming [42]	Accurate representation of discrete and continuous decision variables.	The model is very complex and takes a long time to solve.	Complex systems that need to handle both discrete and continuous variables
	Model predictive control [43]	Real-time optimization, able to foresee future impacts and respond flexibly	Reliance on accurate models and predictions. high computational cost	Suitable for situations where dynamic systems require frequent adjustments
	Robust programming [44]	System uncertainty is taken into account. Improve system resilience and reliability.	Too conservative and sacrificing some performance to cope with the worst scenario.	Scenarios where the environment is uncertain

	Stochastic programming [45]	Ability to handle uncertainty in input data and optimize the decision-making process.	The superiority of the results depends on the accuracy of the probabilistic model.	Input data has a high degree of uncertainty
Metaheuristics method	Evolutionary algorithm [46]	Ability to handle large-scale and complex optimization problems.	Computationally intensive.	Systems with many parameters and complex objective functions.
	Other metaheuristics [47]	Adapt to changing problem structures.	Lack of theoretical convergence guarantees.	Non-linear, non-convex, or mixed problems.

5 5G BS energy trading

Most existing BSMG researches focus on energy consumption modelling and prediction, as well as machine learning approaches to optimize the energy scheduling, little has been done on the energy transactions among multiple BSMGs. The trading schemes in the energy market include bilateral trading, real-time market trading, auction markets, P2P energy trading, virtual power plants, and load aggregation. The existing multi-BSMG energy trading strategies include cooperation strategy and competition strategy. Table 7 summarizes the comparison of different trading strategies.

Table 7. Comparisons of different energy trading strategies.

Type	Strategy	Strengths	Weakness	Application
Single BSMG	Bilateral trading [48]	Transaction terms are clear and risks are controllable.	Less flexible and not be able to respond quickly to market changes.	Energy supply and demand parties who require long-term and stable cooperation.
	Real-time market trading [49]	Highly flexible and able to respond quickly to market changes.	Price fluctuations may be large.	Market environment changes rapidly and requires flexible adjustment.
	Auction markets [50]	High transparency ensures fair competition.	Require complex rules and regulations.	Large-scale energy resource distribution and market participants.
	P2P energy trading [51]	Reduce transaction costs and increases consumer participation.	High technical requirements.	Decentralized energy systems.
	Virtual power plants [52]	Optimize resource use and enhance market competitiveness.	Management is complex and require a high degree of coordination.	Resources are dispersed but require centralized management.
	Demand aggregation [53]	Reduce costs through economies of scale.	Require effective user coordination and management.	Suitable for multi-user concentrated areas, such as commercial areas or residential groups.

Multiple BSMGs	Cooperative trading [54]	Reduce respective costs and risks.	Reduce efficiency and increased dependency.	High market uncertainty
	Competitive trading [55]	Improve efficiency and have price advantage.	Waste of resources and market instability.	Mature market environment, large number of participants and sufficient resources

6 Conclusion

This paper has presented a brief literature review on the structure, BS energy consumption, dispatching optimization and energy trading of the 5G BSMGEMS. Given that the research on BSMGEMS is still quite limited, the following topics are recommended for future investigation.

1) BSs energy consumption analysis and optimization: To develop an effective energy management scheme for BSMGs, it is crucial to understand the energy consumption characteristics of 5G BSs when they are at different working modes, and it is also important to propose more effective optimization tools considering the specific features of the BSs working modes and the volatility and uncertainty of both the renewable power supply and BSs traffic loads.

2) Energy trading and market mechanism: To design suitable energy trading models and mechanisms among different 5G BSMGs, including pricing strategies, trading rules, and market design, has an important role to play in effective energy allocation and utilization. With the roll-out of 5G technology, BSMGs when aggregated, can provide ancillary services to the power grid, such as frequency regulation and standby capacity, and hence improve the overall energy system flexibility and resilience.

3) Environmental and economic assessment: To assess the environmental impact of 5G BSMGs, including carbon footprint calculations and emission reduction strategies to support sustainable development goals is another interest research topic.

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References

1. Zhang, X.D., Ciais, P., Jian, X.H., et al.: The Carbon Footprint Response to Projected Base Stations of China's 5G Mobile Network. Science of the Total Environment, vol. 870, pp. 161906 (2023)
2. Kamiya, G. and Bertoldi, P.: Energy Consumption in Data Centres and Broadband Communication Networks in the EU, Publications Office of the European Union, Luxembourg (2024)
3. Kaur, P., Garg, R., Kukreja, V.: Energy-efficiency schemes for base stations in 5G heterogeneous networks: a systematic literature review. Telecommunication System, vol. 84, pp. 115–151 (2023)
4. Han, J.A., Lin, S.W., Pu, B.Y., Hierarchical Energy Management of DC Microgrid with Photo-voltaic Power Generation and Energy Storage for 5G Base Station. Sustainability,

vol. 16, pp. 2422 (2024)
5. Shurdi, O., Ruci, L., Biberaj, A., et al.: 5G Energy Efficiency Overview. European Scientific Journal, vol. 17, pp. 315 (2021)
6. Kim, T., Lee, S., Choi, H., et al.: An Energy-Efficient Multi-Level Sleep Strategy for Periodic Uplink Transmission in Industrial Private 5G Networks. Sensors, vol. 23, pp. 9070 (2023)
7. Shen, P.F., Shao, Y.L., Cao, Q., et al.: Dynamic gNodeB Sleep Control for Energy-Conserving Radio Access Network. IEEE Transactions on Cognitive Communications and Networking (2024)
8. Wang, X.W., Kang, Q.K., Gao, J., et al.: Distribution Network Restoration Supply Method Considers 5G Base Station Energy Storage Participation. Energy, vol. 289, pp. 129825 (2024)
9. Bao, P., Xu, Q.S., Yang, Y.B.: Modeling and Aggregated Control of Large-scale 5G Base Stations and Backup Energy Storage Systems Towards Secondary Frequency Support. Applied Energy, vol. 357, pp. 122498 (2024)
10. Yan, M., Guo, W.H., Zheng, H.B.: Joint NTP-MAPPO and SDN for Energy Trading among Multi-Base-Station Microgrids. IEEE Internet of Things Journal (2023)
11. Zhou, C.Y., Feng, C., Wang, Y., Spatial-Temporal Energy Management of Base Stations in Cellular Networks. IEEE Internet of Things Journal, vol. 9, pp. 10588-10599 (2021)
12. Ali, A.Z.S., Hussein, A.I., Mohamed, Y.S.: Mohamed Pico and Femto Cells Distribution Effect on User Association Performance in 5G Heterogeneous Networks. Journal of Advanced Engineering Trends, vol. 42, pp. 85-93 (2023)
13. Xu, Y.J., Gui, G., Gacanin, H., et al.: A Survey on Resource Allocation for 5G Heterogeneous Networks: Current Research, Future Trends, and Challenges. IEEE Communications Surveys and Tutorials, vol. 23, pp. 668-695 (2021)
14. Sathya, V., Kala, S. M., Naidu, K.: Heterogenous Networks: From Small Cells to 5G NR-U. Wireless Personal Communications, vol.128, pp. 2779-2810 (2023)
15. Yong, P., Yang, Z.F., Zhang, N., et al.: On the Self-Scheduling of Cellular Base Station Based Virtual Power Plants. IEEE Internet of Things Journal (2024)
16. Zhang, X., Wang, Z., Liao, H.J., et al.: Optimal Capacity Planning and Operation of Shared Energy Storage System for Large-scale Photovoltaic Integrated 5G Base Stations. International Journal of Electrical Power & Energy Systems, vol. 147, pp. 108816 (2023)
17. Zeng, B., Zhang, W.X., Hu, P.D., et al.: Synergetic Renewable Generation Allocation and 5G Base Station Placement for Decarbonizing Development of Power Distribution System: A Multi-objective Interval Evolutionary Optimization Approach. Applied Energy, vol. 351, pp. 121831 (2023)
18. Zhou, Y.Y., Wang, Q.G., Zou, Y., et al.: Voltage Profile Optimization of Active Distribution Networks Considering Dispatchable Capacity of 5G Base Station Backup Batteries. Journal of Modern Power Systems and Clean Energy, vol. 11, pp. 1842-1856 (2023)
19. Baidas, M.W., Hasaneya, R.W., Kamel, R.M., et al.: Solar-Powered Cellular Base Stations in Kuwait: A Case Study. Energies, vol. 14, pp. 7494 (2021)
20. Yu, K.P., Yang, L., Zhang, L.X., et al: Summary of Research on Key Technologies of 5G Base Station Flexible Resources. 2023 8th Asia Conference on Power and Electrical Engineering (ACPEE), pp. 2129-2133 (2023)
21. Zou, H.L., Mao, S.W., Wang Y., et al.: A Survey of Energy Management in Interconnected Multi-Microgrids. IEEE Access, vol.7, pp. 72158-72169 (2019)
22. Arefifar, S.A., Ordonez, M., Mohamed, Y.A.R.I.: Energy Management in Multi-Microgrid Systems—Development and Assessment. IEEE Transactions on Power Systems, vol. 32, pp. 910-922 (2017)

23. Nawaz, A., Zhou, M., Wu, J., et al.: A Comprehensive Review on Energy Management, Demand Response, and Coordination Schemes Utilization in Multi-Microgrids Network. Applied Energy, vol. 323, pp. 119596 (2022)
24. Guan, Y.J., Wei, B.Z., Guerrero, J.M., et al.: An Overview of the Operation Architectures and Energy Management System for Multiple Microgrid Clusters. iEnergy, vol. 306, pp. 306-314 (2022)
25. Saha, D., Bazmohammadi, N., Vasquez, J.C., et al.: Multiple Microgrids: A Review of Architectures and Operation and Control Strategies. Energies, vol. 16, pp. 600 (2023)
26. Sharma, P., Mathur, H.D., Mishra, P.A., et al.: A Critical and Comparative Review of Energy Management Strategies for Microgrids. Applied Energy, vol. 327, pp. 120028 (2022)
27. Battula, A.R., Vuddanti, S., Salkuti, S.R.: Review of Energy Management System Approaches in Microgrids. Energies, vol. 14, pp. 5459 (2021)
28. Marzal, S., Salas, R., González-Medina, R., et al.: Current Challenges and Future Trends in the Field of Communication Architectures for Microgrids. Renewable & Sustainable Energy Reviews, vol. 82, pp. 3610-3622 (2018)
29. Zhou, Q., Shahidehpour, M., Paaso, A., et al.: Distributed Control and Communication Strategies in Networked Microgrids. IEEE Communications Surveys and Tutorials, vol. 22, pp. 2586-2633 (2020)
30. Sheykhi, N., Salami, A., Guerrero, J.M., et al.: A Comprehensive Review on Telecommunication Challenges of Microgrids Secondary Control. International Journal of Electrical Power & Energy Systems, vol. 140, pp. 108081 (2022)
31. Serban, I., Céspedes, S., Marinescu, C., et al.: Communication Requirements in Microgrids: A Practical Survey. IEEE Access, vol. 8, pp. 47694-47712 (2020)
32. Gutierrez-Rojas, D., Nardelli, P.H.J., Mendes, G., et al.: Review of the State of the Art on Adaptive Protection for Microgrids Based on Communications. IEEE Transactions on Industrial Informatics, vol. 17, pp. 1539-1552 (2021)
33. Villanueva-Rosario, J.A., Santos-García, F., Aybar-Mejía, M.E., et al.: Coordinated Ancillary Services, Market Participation and Communication of Multi-Microgrids: A Review. Applied Energy, vol. 308, pp. 118332 (2022)
34. Dong, W., Yang, Q., Fang, X.L., et al.: Adaptive Optimal Fuzzy Logic Based Energy Management in Multi-Energy Microgrid Considering Operational Uncertainties. Applied Soft Computing, vol. 98, pp. 106882 (2021)
35. Javanmard, B., Tabrizian, M., Ansarian M., et al.: Energy Management of Multi-Microgrids Based on Game Theory Approach in the Presence of Demand Response Programs, Energy Storage Systems and Renewable Energy Resources. Journal of Energy Storage, vol. 42, pp. 102971 (2021)
36. Jabeur, R., Boujoudar, Y., Azeroual, M., et al.: Microgrid Energy Management System for Smart Home Using Multi-Agent System. International Journal of Electrical and Computer Engineering (IJECE), vol. 12, pp. 1153-1160 (2022)
37. Samuel, O., Javaid, N., Khalid, A., et al.: Towards Real-Time Energy Management of Multi-Microgrid Using a Deep Convolution Neural Network and Cooperative Game Approach. IEEE Access, vol. 8, pp. 161377-161395 (2020)
38. Alabdullah, M.H., Abido, M.A.: Microgrid Energy Management Using Deep Q-Network Reinforcement Learning. Alexandria Engineering Journal, vol. 61, pp. 9069-9078 (2022)
39. Singh, A.R., Ding, L., Raju, D.K., et al.: A Swarm Intelligence Approach for Energy Management of Grid-Connected Microgrids with Flexible Load Demand Response. International Journal of Energy Research, vol. 46, pp. 4301-4319 (2022)
40. Mirzaei, M., Keypour, R., Savaghebi, M., et al.: Probabilistic Optimal Bi-level Scheduling of a Multi-Microgrid System with Electric Vehicles. Journal of Electrical Engineering &

Technology, vol. 15, pp. 2421-2436 (2020)
41. Zeng, P., Li, H.P., He, H.B., et al.: Dynamic Energy Management of a Microgrid Using Approximate Dynamic Programming and Deep Recurrent Neural Network Learning. IEEE Transactions on Smart Grid, vol. 10, pp. 4435-4445 (2019)
42. Sigalo, M.B., Pillai, A.C., Das, S., et al.: An Energy Management System for the Control of Battery Storage in a Grid-Connected Microgrid Using Mixed Integer Linear Programming. Energies, vol. 14, pp. 6212 (2021)
43. Zhao, Z.L., Guo, J.T., Luo, X., et al.: Distributed Robust Model Predictive Control-Based Energy Management Strategy for Islanded Multi-Microgrids Considering Uncertainty. IEEE Transactions on Smart Grid, vol. 13, pp. 2107-2120 (2022)
44. Gil-González, W., Montoya, O.D., Hernández, J.C.: An Energy Management System for the Optimal Operation of BESS in DC Microgrids: A Robust Convex Programming Approach. IEEE Access, vol. 11, pp. 38168-38181 (2023)
45. Wang, S.S., Gangammanavar, H., Eksioglu, S.D., et al.: Stochastic Optimization for Energy Management in Power Systems with Multiple Microgrids. IEEE Transactions on Smart Grid, vol. 10, pp. 1068-1079 (2019)
46. Keshta, H.E., Malik, O.P., Saied, E.M., et al.: Energy Management System for Two Islanded Interconnected Micro-Grids Using Advanced Evolutionary Algorithms. Electric Power Systems Research, vol. 192, pp. 106958 (2021)
47. Suresh, V., Janik, P., Jasinski, M., et al.: Microgrid Energy Management Using Metaheuristic Optimization Algorithms. Applied Soft Computing, vol. 134, pp. 109981 (2023)
48. Van Leeuwen, G., AlSkaif, T., Gibescu, M., et al.: An Integrated Blockchain-Based Energy Management Platform with Bilateral Trading for Microgrid Communities. Applied Energy, vol. 263, pp. 114613 (2020)
49. Marzband, M., Sumper, A., Ruiz-Alvarez, A., et al.: Experimental Evaluation of a Real Time Energy Management System for Stand-Alone Microgrids in Day-Ahead Markets. Applied Energy, vol. 106, pp. 365-376 (2013)
50. Ul Hassan, M., Rehmani, M.H., Chen, J.J.: DEAL: Differentially Private Auction for Blockchain-Based Microgrids Energy Trading. IEEE Transactions on Services Computing, vol. 13, pp. 263-275 (2020)
51. Zhang, C.H., Wu, J.Z., Zhou, Y., et al.: Peer-to-Peer Energy Trading in a Microgrid. Applied Energy, vol. 220, pp. 1-12 (2018)
52. Minai, A.F., Khan, A.A., Kitmo, et al.: Evolution and Role of Virtual Power Plants: Market Strategy with Integration of Renewable Based Microgrids. Energy Strategy Reviews, vol. 53, pp. 101390 (2024)
53. Gregori, M., Matamoros, J., Gregoratti, D.: Demand Response Aggregators in Microgrid Energy Trading. 2016 IEEE Global Conference on Signal and Information Processing (GlobalSIP), pp. 921-925 (2016)
54. Chen, W.D., Wang, J.N., Yu, G.Y., et al.: Research on Day-Ahead Transactions Between Multi-Microgrid Based on Cooperative Game Model. Applied Energy, vol. 316, pp. 119106 (2022)
55. Lin, Y., Dong, P., Sun, X.L., et al.: Two-Level Game Algorithm for Multi-Microgrid in Electricity Market. IET Renewable Power Generation, vol. 11, pp. 1733-1740 (2017)