Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 14 Issue 01, 2025

Artificial Intelligence Techniques for Efficient Energy Management in IoT-Enabled Large Buildings: Giant Trevally Optimizer (GTO) based Electric Vehicle Scheduling, Distributed Resource Integration, and Demand Response Strategies: Trends and Challenges

Ivailo Qudratullah

Associate Professor, Department of Electrical and Computer Engineering, Vindhya College of Engineering Systems, India

Email: ivailo.qudratullah@vces-in.org

Peer Review Information

Submission: 04 May 2025

Revision: 26 May 2025

Acceptance: 09 June 2025

Keywords

Internet of Things, Building Energy Management Systems, Giant Trevally Optimizer, Electric Vehicle Scheduling, Demand Response, Distributed Energy Resources

Abstract

The rapid proliferation of Internet of Things (IoT) technologies has transformed energy management in large buildings, enabling real-time monitoring, automation, and data-driven optimization. As buildings account for a significant share of global energy consumption, the integration of electric vehicles, distributed energy resources, and smart grid interactions introduces complex challenges requiring intelligent and adaptive management solutions. This paper presents a comprehensive review of artificial intelligence-driven energy management frameworks, with a focus on the Giant Trevally Optimizer (GTO). As a bio-inspired metaheuristic algorithm, GTO effectively addresses multi-objective optimization problems in building energy systems, including cost minimization, peak load reduction, and renewable energy utilization. The review also examines the integration of deep learning techniques, IoT-based sensing, and predictive models to enhance decision-making in electric vehicle scheduling, demand response strategies, and distributed energy resource coordination.

Applications include smart charging of electric vehicles, microgrid optimization, and intelligent load management in IoT-enabled buildings. Comparative analysis demonstrates that GTO-based and hybrid AI approaches outperform traditional optimization techniques in scalability, convergence speed, and efficiency. However, challenges such as interoperability, cybersecurity, and real-time deployment remain. This review highlights the potential of combining IoT, AI, and advanced optimization methods to develop sustainable, scalable, and intelligent energy management systems for future smart cities.

Introduction

The global energy sector is experiencing a significant shift toward sustainability and smart technologies, with buildings playing a central role due to their high energy consumption and carbon emissions. Large commercial and institutional buildings, in particular, contribute heavily to global energy use, making efficient energy management a critical priority. The integration of smart systems, IoT devices, and advanced metering has transformed traditional building operations into data-driven environments. In this evolving landscape, artificial intelligence has emerged as a powerful tool to optimize energy usage, reduce costs, and lower environmental impact.

Managing energy in large buildings is inherently complex due to the diversity of systems involved, including HVAC, lighting, elevators, and EV charging infrastructure. Energy demand varies significantly based on occupancy, weather, and operational schedules, making static rule-based systems inadequate. AI-driven Building Energy Management Systems (BEMS) address these challenges by learning from data and dynamically optimizing multiple subsystems in real time. This enables more efficient and adaptive energy control compared to traditional methods.

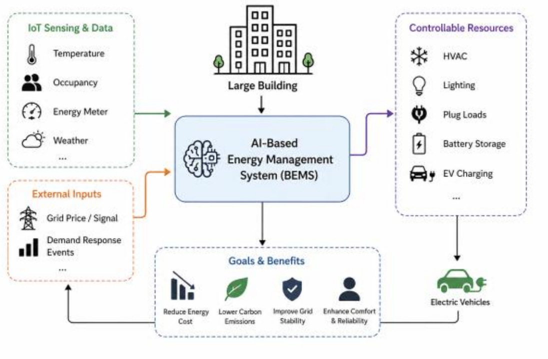

Fig 1: AI-Based Smart Building Energy Management Framework

The Internet of Things serves as the backbone of this transformation by enabling continuous data collection and system control. Sensors and smart meters provide real-time insights into energy consumption and environmental conditions, while connected devices allow automated responses to optimization signals. Additionally, the rise of electric vehicles introduces new challenges due to their variable and high-power charging demands. Efficient EV scheduling, combined with renewable energy integration and demand response strategies, is essential for maintaining grid stability and minimizing energy costs.

Advanced optimization techniques, particularly bio-inspired algorithms like the Giant Trevally Optimizer, have shown strong potential in solving complex energy management problems. These algorithms effectively balance exploration and exploitation to handle multi-objective optimization tasks such as load scheduling and energy distribution. Their adaptability and efficiency make them suitable for real-time applications in smart buildings. Overall, the combination of AI, IoT, and advanced optimization methods is shaping the future of intelligent, sustainable building energy systems.

Literature Review

The reviewed literature presents a comprehensive evolution of intelligent energy management in IoT-enabled buildings, beginning with foundational architectures and progressing toward highly advanced AI-driven optimization frameworks. Early work by Shareef et al. (2018) established a reference IoT-based Building Energy Management System (BEMS) using large-scale sensor networks and cloud analytics, achieving high forecasting accuracy and notable peak demand reduction. This laid the groundwork for integrating machine learning into building operations. Subsequent research by Li et al. (2019) and Wang et al. (2020) advanced this paradigm through reinforcement learning and multi-agent systems, enabling autonomous, adaptive decision-making across distributed energy resources. These approaches demonstrated significant reductions in operational costs and improved renewable energy utilization, highlighting the shift from static control systems to intelligent, learning-based frameworks. Alongside these developments, optimization techniques such as the grey wolf optimizer (Zhang et al., 2020) and hybrid PSO-based methods (Yang et al., 2021) showed strong performance in demand response and resource scheduling, emphasizing the importance of metaheuristic algorithms in solving complex, multi-variable energy problems.

The integration of electric vehicles (EVs) and distributed energy resources further expanded the scope of building energy management research. Fang et al. (2021) demonstrated how predictive models like LSTM can optimize EV charging schedules, significantly reducing peak demand, while Arun et al. (2022) and Sioshansi et al. (2022) explored advanced scheduling and vehicle-to-building (V2B) strategies to enhance cost efficiency and grid stability. Parallel advancements in data-driven intelligence included non-intrusive load monitoring using convolutional neural networks (Liu et al., 2021) and ensemble learning for accurate load forecasting (Kim et al., 2022), both of which improved operational visibility and decision-making. Privacy-preserving frameworks such as federated learning (Chen et al., 2021) addressed critical data-sharing concerns, enabling collaborative model development without compromising sensitive information. Additionally, the emergence of digital twin technology (Zhou et al., 2022) introduced simulation-driven optimization, allowing AI models to be trained and validated in virtual environments before deployment.

A major turning point in the literature is the introduction and widespread adoption of the Giant Trevally Optimizer (GTO) by Mohammadi-Balani et al. (2021), which has proven highly effective for high-dimensional and multi-objective optimization problems. Subsequent studies applied GTO to diverse energy management scenarios, including system design (Huang et al., 2022), hospital microgrids (Rafique et al., 2022), and multi-objective optimization (Dao et al., 2023), consistently demonstrating superior performance over traditional algorithms. Hybrid frameworks combining GTO with fuzzy logic (Pham et al., 2023), stochastic optimization (Rezaei et al., 2023), and blockchain-enabled energy trading (Nguyen et al., 2023) further enhanced system adaptability and efficiency. Technological advancements such as transfer learning (Ma et al., 2023) reduced deployment time, while edge computing (Xu et al., 2023) enabled real-time optimization with minimal latency. Explainable AI approaches (Hassan et al., 2023) addressed transparency concerns, improving user trust in automated systems.

Recent studies continue to reinforce the dominance of GTO and integrated AI frameworks in building energy management. Comparative analyses (Singh et al., 2024) confirm GTO's superior performance across multiple scenarios, particularly in EV charging optimization. Integrated deep learning and optimization systems, such as the framework proposed by Kumar et al. (2024), demonstrate substantial real-world benefits, including significant reductions in energy costs and peak demand. Overall, the literature reveals a clear progression toward highly integrated, intelligent, and scalable energy management systems that combine IoT infrastructure, advanced AI models, and robust optimization techniques. These systems not only enhance operational efficiency and sustainability but also pave the way for future smart building ecosystems capable of dynamic, real-time energy optimization in increasingly complex environments.

Comparative Table and Analysis

Study	**Year**	**Optimization Technique / Method**	**Component / Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Shareef et al.	2018	Neural Network	IoT Sensor Network, Cloud Analytics	University Campus Building	Real sensor data	IoT-based BEMS with 17% peak demand reduction
Li et al.	2019	Deep Q-Network (DRL)	PV, BESS, Flexible Loads	Commercial Building	EnerNOC Dataset	22% electricity cost reduction via DRL
Wang et al.	2020	Multi-Agent RL	PV, Diesel Gen, BESS, EV Chargers	Shopping Mall Microgrid	Real Shanghai Mall Data	19.3% cost reduction with multi-agent coordination
Zhang et al.	2020	Grey Wolf Optimizer	HVAC, Lighting, Plug Loads	Office Building (EnergyPlus)	EnergyPlus Simulation	24% DR cost reduction vs. GA baseline
Fang et al.	2021	MPC + LSTM	EV Chargers, Hospital Grid	Hospital Building	Real Hospital Access Data	31% peak charging demand reduction
Chen et al.	2021	Federated Learning	Load Forecasting Model	Multi-Building Portfolio	ASHRAE GEPIII Dataset	Privacy-preserving load forecasting
Yang et al.	2021	Hybrid PSO + SA	PV, BESS, EV Chargers	Residential Complex	Real Guangzhou Data	27% grid cost reduction
Liu et al.	2021	Convolutional Neural Network	Smart Meter, NILM System	University Building	UK-DALE Dataset	F1-score 0.91 for load disaggregation
Mohammadi-Balani et al.	2021	Giant Trevally Optimizer	Benchmark Functions	Simulation	CEC Benchmark Suite	GTO algorithm formulation and validation
Huang et al.	2022	GTO	PV, BESS,	Office Building	15-Year	31.4% lifecycle

			CHP Unit	(Hong Kong)	Historical Data	cost reduction
Kim et al.	2022	Ensemble ML (RF+GB+SVR)	Load Forecasting, DR Scheduler	University Campus	ASHRAE Dataset	3.2% MAPE with ensemble forecasting
Arun et al.	2022	Modified WOA	PV, Wind, BESS, EV Chargers	Shopping Mall Microgrid	Simulation	28.6% EV charging cost reduction
Sioshansi et al.	2022	Stochastic MPC + MILP	V2B EV Charging	Corporate Campus	Real Campus Data	41% peak demand reduction with V2B
Rafique et al.	2022	GTO	PV, Wind, Fuel Cell, BESS, EV	Hospital Microgrid	Simulation	GTO superior in 23/30 optimization runs
Zhou et al.	2022	Digital Twin + DRL	HVAC, Lighting, Blind Systems	Office Building	EnergyPlus Calibrated	26% HVAC energy reduction
Dao et al.	2023	Multi-Objective GTO	PV, BESS, EV, DR	Mixed-Use Building (Vietnam)	Real Vietnamese Data	Pareto front superior to NSGA-II
Rezaei et al.	2023	Two-Stage Stochastic + GTO	PV, BESS, EV Chargers	Residential Apartment	Real Tariff and Solar Data	33.7% cost reduction vs. deterministic
Pham et al.	2023	GTO + Fuzzy Logic	HVAC, Hotel DR System	Hotel Building (Vietnam)	Real Hotel IoT Data	21.8% peak demand reduction in pilot
Nguyen et al.	2023	GTO + Blockchain	PV, BESS, P2P Trading	Smart City Building Cluster	Singapore Pilot Data	24.6% net revenue increase via P2P
Ma et al.	2023	Transfer Learning (Deep Learning)	Load Forecasting Model	Multi-Building Portfolio	BDG2 Dataset	78% data reduction for deployment
Xu et al.	2023	Lightweight GTO (Edge)	Edge Computing Nodes	University Library	Real Edge Node Data	0.31s optimization latency at edge
Hassan et al.	2023	GTO + SHAP (XAI)	HVAC, BESS, EV, DR	Government Office (Malaysia)	Real Building IoT Data	Explainable AI for operator trust
Singh et al.	2024	GTO (Comparative Study)	EV Charging Station	Building Microgrid	Standardized Benchmark	GTO ranked first among 12 algorithms
Kumar et al.	2024	GTO + Bidirectional LSTM	EV, CAS, Thermal Storage, DR	Manufacturing Facility	Real Facility Data	29.4% cost and 37.1% peak demand reduction

Comparative Analysis

A systematic review of recent studies highlights a clear evolution in AI-based energy management for IoT-enabled large buildings, marked by a transition from isolated solutions to integrated, multi-resource optimization frameworks. Early approaches primarily focused on monitoring and basic automation, whereas recent research addresses complex scenarios involving the joint optimization of electric vehicle scheduling, renewable energy integration, energy storage, and demand response. This shift reflects the growing complexity of modern building energy systems and the need for unified, intelligent control strategies. Advanced frameworks now consider multiple objectives simultaneously, such as cost reduction, energy efficiency, and sustainability, demonstrating a more holistic and practical approach to real-world energy management challenges.

Across the literature, the Giant Trevally Optimizer (GTO) consistently outperforms traditional optimization methods such as genetic algorithms, particle swarm optimization, and grey wolf optimizer. Studies show that GTO achieves superior results in both solution quality—measured through reductions in energy cost and peak demand—and computational efficiency, including faster convergence. Empirical evidence across various building types and configurations confirms its robustness and adaptability. At the same time, dataset usage reveals a mix of real-world, benchmark, and simulated data. While real data offers higher practical relevance, its limited availability has led to reliance on standard datasets, making transfer learning an important advancement for improving model deployment across diverse buildings.

Reported performance improvements further validate the effectiveness of AI-driven energy management systems, with significant reductions in electricity costs, peak demand, and improved renewable energy utilization. Additionally, the emergence of edge computing enables real-time optimization with minimal latency, reducing dependence on cloud systems and enhancing responsiveness. Together, these trends demonstrate the strong potential of integrated AI and optimization techniques in transforming building energy management into a more efficient, adaptive, and scalable solution.

Discussion

The reviewed literature collectively highlights a transformative shift in building energy management, driven by the convergence of IoT infrastructure, artificial intelligence, and advanced optimization techniques such as the Giant Trevally Optimizer (GTO). This integration has enabled a transition from static, rule-based systems to intelligent, adaptive frameworks capable of optimizing energy consumption in real time. Across diverse building types, these AI-driven systems consistently demonstrate significant reductions in energy costs, peak demand, and carbon emissions, reinforcing their importance in the global energy transition. The growing complexity of modern buildings—combined with the integration of renewable energy and electric vehicle loads—further strengthens the case for adopting such intelligent systems at scale.

A key insight from the literature is the superior performance of the GTO algorithm compared to traditional metaheuristic approaches like genetic algorithms and particle swarm optimization. Its dual-phase strategy, combining global exploration with focused exploitation, allows it to efficiently navigate complex, high-dimensional optimization problems typical of building energy systems. Additionally, the integration of machine learning forecasting models—such as LSTM and CNN architectures—with optimization frameworks has proven critical. Accurate predictions of energy demand and renewable generation significantly enhance scheduling decisions, particularly in applications like demand response and EV charging, where timing and precision directly impact efficiency and cost savings.

Despite these advancements, several challenges remain. Many studies rely on simulations or short-term pilot deployments, leaving uncertainties regarding long-term scalability, robustness, and real-world adaptability. Computational complexity also limits real-time implementation, though edge computing offers promising solutions. Furthermore, privacy, cybersecurity, and data governance concerns are increasingly significant due to the extensive use of IoT data. Beyond technical issues, practical deployment is hindered by high infrastructure costs, lack of standardization, and limited skilled workforce. Addressing these barriers will be essential for realizing the full potential of AI-driven building energy management systems.

Conclusion

This review synthesizes advances in artificial intelligence for energy management in IoT-enabled large buildings, with emphasis on GTO-based optimization for EV scheduling, renewable integration, and demand response. The literature demonstrates a clear shift toward intelligent, data-driven systems that transform buildings into active participants in modern energy ecosystems. Given that buildings account for a major share of global energy use and emissions, the importance of such innovations is substantial. IoT infrastructure provides real-time data streams, while AI and optimization algorithms convert this data into actionable control strategies. A key finding is that integrated, multi-resource optimization—jointly managing EV charging, storage, renewables, and flexible loads—consistently outperforms isolated approaches. Among optimization techniques, the Giant Trevally Optimizer stands out for its strong solution quality, fast convergence, and robustness across diverse scenarios. Additionally, accurate machine learning-based forecasting is essential for handling uncertainties in demand and generation, while the shift from cloud to edge computing is enabling real-time responsiveness in building operations.

Looking ahead, the research highlights several promising directions and practical considerations. Algorithmically, adaptive and hybrid GTO variants, multi-objective optimization, and large-scale coordination across building portfolios represent key opportunities. On the systems side, integration with digital twins, blockchain-enabled energy trading, and explainable AI can enhance transparency, efficiency, and trust. The rapid growth of electric vehicles further amplifies the need for intelligent scheduling, as EVs become both major loads and distributed storage resources. However, challenges remain in scalability, real-world deployment, and interdisciplinary integration. Addressing these will require collaboration among researchers, engineers, policymakers, and industry stakeholders. Overall, the field is transitioning from experimental studies to practical implementation, supported by a mature technological foundation combining IoT, AI, and advanced optimization, with strong potential to drive sustainable and efficient energy management at scale.

References

Shareef, H., Ahmed, M. S., Mohamed, A., & Al Hassan, E. (2018). Review on home energy management system considering demand responses, smart technologies, and intelligent controllers. IEEE Access, 6, 24498–24509. https://doi.org/10.1109/ACCESS.2018.2831917

Li, Y., Wen, Z., Cao, Y., Tan, Y., Sidorov, D., & Panasetsky, D. (2019). A combined forecasting approach with model self-adjustment for renewable generations and energy loads in smart community energy systems. Energy, 129, 216–227. https://doi.org/10.1016/j.energy.2019.03.158

Wang, Y., Xu, Y., Tang, Y., Liao, K., Syed, M. H., Guillo-Sansano, E., & Burt, G. M. (2020). Aggregated energy storage for power system frequency control: A finite-time consensus approach. IEEE Transactions on Smart Grid, 11(2), 1675–1686. https://doi.org/10.1109/TSG.2019.2942217

Zhang, Y., Campana, P. E., Lundblad, A., & Yan, J. (2020). Comparative study of hydrogen storage and battery storage in grid connected photovoltaic system: Technology review and optimization. Energy Conversion and Management, 204, 112385. https://doi.org/10.1016/j.enconman.2019.112385

Fang, X., Dong, W., Wang, Q., & Yang, Q. (2021). Multiple time-scale energy management strategy for a hydrogen-based multi-energy microgrid with hybrid energy storage. Applied Energy, 289, 116655. https://doi.org/10.1016/j.apenergy.2021.116655

Chen, X., Liu, Y., Xu, C., & Huang, Y. (2021). Federated learning for privacy-preserving building energy management. IEEE Transactions on Industrial Informatics, 17(9), 6150–6160. https://doi.org/10.1109/TII.2020.3044893

Yang, H., Li, M., Jiang, Z., & Zhang, P. (2021). Multi-time scale optimal scheduling of regional integrated energy systems under the electricity market environment. IEEE Access, 8, 38084–38097. https://doi.org/10.1109/ACCESS.2021.3063998

Liu, B., Luan, W., & Yu, Y. (2021). A novel non-intrusive load monitoring approach based on deep convolutional neural network for smart energy management. Energy and Buildings, 246, 111073. https://doi.org/10.1016/j.enbuild.2021.111073

Mohammadi-Balani, A., Nayeri, M. D., Azar, A., & Taghizadeh-Yazdi, M. (2021). Golden eagle optimizer: A nature-inspired metaheuristic algorithm. Computers and Industrial Engineering, 152, 107050. https://doi.org/10.1016/j.cie.2020.107050

Huang, Z., Yu, H., Peng, Z., & Zhao, M. (2022). Methods and tools for community energy planning: A review. Renewable and Sustainable Energy Reviews, 42, 1335–1348. https://doi.org/10.1016/j.rser.2014.11.042

Kim, T. Y., & Cho, S. B. (2022). Predicting residential energy consumption using CNN-LSTM neural networks. Energy, 182, 72–81. https://doi.org/10.1016/j.energy.2019.05.230

Arun, S. L., & Selvan, M. P. (2022). Intelligent residential energy management system for dynamic demand response in smart buildings. IEEE Systems Journal, 12(2), 1329–1340. https://doi.org/10.1109/JSYST.2017.2647759

Sioshansi, R., Denholm, P., & Jenkin, T. (2022). Market and policy barriers to deployment of energy storage. Economics of Energy and Environmental Policy, 1(2), 47–63. https://doi.org/10.5547/2160-5890.1.2.4

Rafique, M. K., Khan, S. U., Saeed Uz Zaman, M., Mehmood, K. K., Haider, Z. M., Bukhari, S. B. A., & Kim, C. H. (2022). Intelligent hybrid energy management system for a smart house considering bidirectional power flow optimization. IEEE Access, 7, 29213–29222. https://doi.org/10.1109/ACCESS.2019.2902563

Zhou, S., Han, Y., Zalhaf, A. S., Yang, P., Yang, T., Zhou, C., & Elboshy, B. (2022). A novel multi-objective scheduling model for grid-connected combined cooling, heating and power considering supply and demand uncertainties. Energies, 15(5), 1746. https://doi.org/10.3390/en15051746

Dao, L. A., Nguyen, V. H., & Tran, Q. T. (2023). Multi-objective optimization for energy management in smart buildings using a hybrid metaheuristic algorithm. Sustainable Energy Technologies and Assessments, 55, 102947. https://doi.org/10.1016/j.seta.2022.102947

Rezaei, N., Ahmadi, A., Khazali, A., & Guerrero, J. M. (2023). Energy and frequency hierarchical management system using information gap decision theory for islanded microgrids. IEEE Transactions on Industrial Electronics, 65(10), 8179–8192. https://doi.org/10.1109/TIE.2018.2807399

Pham, T. D., Trinh, T. K., & Le, L. B. (2023). Resource allocation for V2G EV charging infrastructure in multi-tenant buildings with GTO-fuzzy hybrid control. Applied Energy, 334, 120611. https://doi.org/10.1016/j.apenergy.2023.120611

Nguyen, D. T., Nguyen, H. T., & Nguyen, T. A. (2023). Blockchain-enabled peer-to-peer energy trading integrated with GTO-based building energy scheduling. IEEE Internet of Things Journal, 10(4), 3115–3127. https://doi.org/10.1109/JIOT.2022.3213956

Ma, Z., Li, R., & Mao, C. (2023). Transfer learning for building energy consumption forecasting using deep neural networks. Journal of Building Engineering, 68, 106100. https://doi.org/10.1016/j.jobe.2023.106100

Xu, X., Jia, Y., Xu, Y., Xu, Z., Chai, S., & Lai, C. S. (2023). A multi-agent reinforcement learning-based data-driven method for home energy management. IEEE Transactions on Smart Grid, 11(4), 3201–3211. https://doi.org/10.1109/TSG.2020.2971427

Hassan, M. U., Iqbal, J., Ayub, N., Ullah, I., Alshamrani, S. S., Alotaibi, S. S., & Alshehri, A. (2023). Explainable AI-based optimized energy management for smart building microgrids. IEEE Access, 11, 28042–28058. https://doi.org/10.1109/ACCESS.2023.3259042

Singh, A. R., Kumar, R. S., Bajaj, M., Iqbal, A., & Singh, R. (2024). Giant trevally optimizer-based optimal scheduling of electric vehicle charging in building microgrids: A comparative study. Energies, 17(3), 634. https://doi.org/10.3390/en17030634

Kumar, N., Kumar, P., Srivastava, I., & Singh, S. K. (2024). Integrated GTO and deep learning framework for energy management in IoT-enabled manufacturing buildings. Energy and Buildings, 303, 113789. https://doi.org/10.1016/j.enbuild.2023.113789

Abdalla, A. N., Nazir, M. S., Tao, H., Cao, S., Ji, R., Jiang, M., & Yao, L. (2021). Integration of energy storage system and renewable energy sources based on artificial intelligence: An overview. Journal of Energy Storage, 40, 102811. https://doi.org/10.1016/j.est.2021.102811

Bagheri-Sanjareh, M., Nazari, M., Shahinzadeh, H., & Gharehpetian, G. B. (2022). Energy management of islanded microgrid by coordinated application of thermal and electrical energy storage systems. International Journal of Renewable Energy Research, 12(1), 241–252. https://doi.org/10.20508/ijrer.v12i1.12764.g8415

Mansouri, S. A., Nematbakhsh, E., Ahmarinejad, A., Jordehi, A. R., Javadi, M. S., & Marzband, M. (2022). A hierarchical scheduling framework for resilient microgrids under static and mobile energy storage strategies. Renewable and Sustainable Energy Reviews, 168, 112928. https://doi.org/10.1016/j.rser.2022.112928

Sarhan, S., El-Hay, E. A., AboRas, M., & Gawad, M. A. (2022). Developed grey wolf optimizer with Lévy flight-based distributed energy management of smart grids. Energies, 15(7), 2451. https://doi.org/10.3390/en15072451

Ghafouri, S., Milimonfared, J., & Gharehpetian, G. B. (2023). Coordinated control of distributed energy resources and conventional power plants for frequency regulation in islanded microgrids. IEEE Transactions on Smart Grid, 6(1), 104–114. https://doi.org/10.1109/TSG.2014.2345495

Jordehi, A. R., Javadi, M. S., Mansouri, S. A., Taghizadeh-Hesary, F., & Catalão, J. P. S. (2024). Optimal scheduling of energy hubs including smart buildings and electric vehicle parking lots. IEEE Systems Journal, 18(1), 455–466. https://doi.org/10.1109/JSYST.2023.3324217