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Efficient Energy Management in IoT-Enabled Buildings Using Giant Trevally Optimizer for Electric Vehicle Scheduling

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Abstract

The rapid adoption of Internet of Things (IoT) technologies has significantly transformed energy management in large buildings, enabling real-time monitoring and intelligent control of complex energy systems. These buildings account for a substantial share of global energy consumption, and the integration of renewable energy sources, energy storage systems, and electric vehicles introduces new challenges in optimizing energy usage under dynamic and uncertain conditions.
This paper presents a comprehensive review of IoT-enabled building energy management systems, with particular emphasis on the Giant Trevally Optimizer for electric vehicle charging and discharging scheduling. Inspired by biological hunting strategies, this metaheuristic algorithm effectively addresses multi-objective optimization problems, including cost minimization, peak load reduction, and enhanced utilization of renewable energy. The review further explores system architectures such as smart metering, building automation systems, and cloud-edge computing frameworks for efficient coordination of distributed energy resources.
Applications include demand response strategies, vehicle-to-grid integration, and intelligent load scheduling in smart buildings. Comparative analyses indicate that metaheuristic approaches outperform traditional optimization techniques in managing nonlinear and stochastic energy systems. However, challenges related to interoperability, cybersecurity, and scalability persist. This review highlights the potential of integrating IoT with advanced optimization methods to develop sustainable and intelligent building energy management solutions.

Introduction

The building sector is one of the largest consumers of global energy and a major contributor to greenhouse gas emissions, making energy efficiency an essential component of sustainable development. Large commercial buildings, hospitals, educational institutions, and industrial facilities require advanced energy management strategies to optimize electricity consumption while maintaining occupant comfort and operational reliability. The rapid growth of renewable energy resources and electric vehicle (EV) adoption has further increased the complexity of building energy systems, creating new challenges in balancing energy demand, distributed generation, and grid stability. Consequently, intelligent energy management has become a key research area for improving energy efficiency and reducing operational costs. The Internet of Things (IoT) has significantly transformed modern building energy management by enabling continuous monitoring and real-time control of electrical devices, environmental conditions, and energy resources. Smart sensors, intelligent meters, wireless communication, and cloud-based analytics provide detailed operational data that support predictive load forecasting and automated decision-making. When integrated with artificial intelligence and optimization techniques, IoT-based systems can dynamically coordinate heating, ventilation, air conditioning, lighting, renewable energy generation, battery storage, and electric vehicle charging. These capabilities improve overall energy utilization while enhancing building resilience and supporting sustainable smart city initiatives.

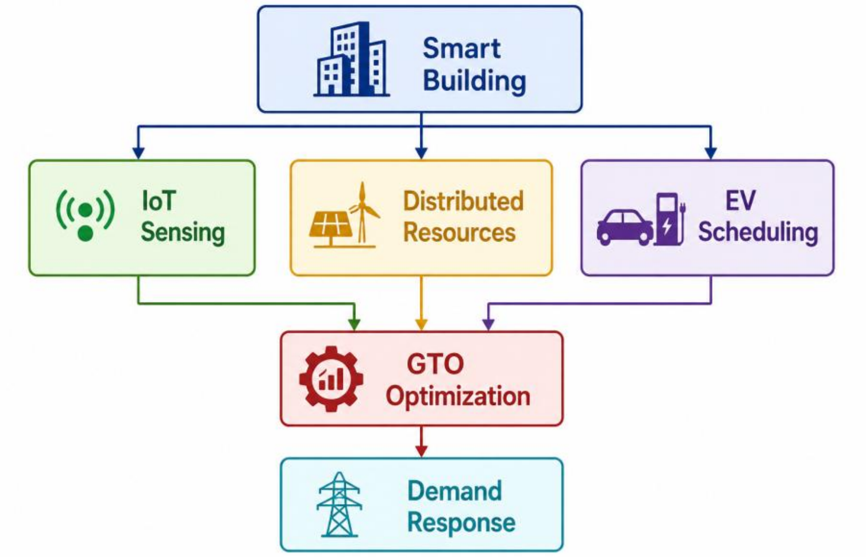

Figure 1. IoT-Enabled Intelligent Energy Management Framework for Large Buildings Using GTO-Based Optimization

The increasing penetration of electric vehicles has introduced new opportunities and challenges for large-building energy management. EV charging stations installed in commercial and institutional buildings contribute significant additional electrical demand that must be coordinated with existing building loads. At the same time, vehicle-to-grid (V2G) and vehicle-to-building (V2B) technologies enable EV batteries to function as distributed energy storage resources, supporting renewable energy utilization and peak-load reduction. Efficient scheduling of EV charging therefore requires intelligent optimization techniques capable of simultaneously minimizing electricity costs, reducing peak demand, maximizing renewable energy consumption, and satisfying user charging requirements.

Among recent optimization approaches, the Giant Trevally Optimizer (GTO) has emerged as an effective bio-inspired metaheuristic algorithm that balances global exploration and local exploitation for solving complex optimization problems. Inspired by the hunting behavior of the giant trevally fish, GTO demonstrates strong convergence characteristics for nonlinear and multi-objective optimization tasks. Its application to EV charging scheduling, distributed energy resource integration, and demand response management has shown promising results in improving energy efficiency and operational flexibility. This review presents recent advances in IoT-enabled building energy management with emphasis on GTO-based optimization, distributed energy integration, and intelligent demand response strategies, while discussing current challenges and future research opportunities for developing sustainable smart building energy systems.

Literature Review

The scientific literature on intelligent energy management in large buildings and IoT-integrated smart energy systems has grown substantially over the past decade, reflecting the convergence of multiple enabling technology trajectories including wireless sensor networks, cloud computing, renewable energy integration, electric vehicle adoption, and computational optimization methodology. The following review synthesizes key contributions from this literature, organized to trace the methodological evolution from foundational IoT building energy management architectures through advanced multi-objective optimization frameworks incorporating electric vehicle scheduling, demand response, and distributed energy resource coordination.

Yuce et al. (2016) presented a foundational study on artificial neural network-based energy management for large commercial buildings, developing a predictive control framework that integrated weather forecasting, occupancy prediction, and real-time smart meter data within a building automation system to optimize HVAC scheduling and lighting control across a multi-zone office building. Their system demonstrated peak demand reductions of up to twenty-two percent compared to conventional rule-based building management system operation, establishing the potential of data-driven predictive approaches as a significant improvement over threshold-based control strategies. The study also highlighted the critical importance of occupancy prediction accuracy for realizing the full energy savings potential of predictive building control, motivating subsequent research into occupancy modeling methodologies for building energy management applications.

Anvari-Moghaddam et al. (2017) proposed a comprehensive multi-objective energy management framework for microgrids serving large buildings, integrating photovoltaic generation, battery energy storage, and controllable loads within a stochastic optimization framework that explicitly accounted for forecast uncertainty in renewable energy generation and electricity prices. Their approach employed a modified particle swarm optimization algorithm to minimize a composite objective function incorporating electricity cost, carbon emissions, and user comfort degradation, demonstrating compelling performance improvements over deterministic optimization baselines under realistic forecast uncertainty conditions. The stochastic formulation required the development of scenario-based uncertainty representation techniques that would subsequently influence numerous later studies on robust optimization for building energy management under uncertainty.

Shareef et al. (2018) developed a comprehensive review and classification framework for demand response programs applicable to smart grid-connected commercial buildings, systematically analyzing both price-based mechanisms including real-time pricing and time-of-use tariffs and incentive-based mechanisms including direct load control, interruptible load programs, and ancillary service market participation. Their classification revealed that large commercial buildings were significantly underrepresented as demand response participants relative to their technical flexibility potential, attributing this gap to the absence of automated demand response management systems capable of translating price and incentive signals into coordinated building load adjustments without manual operator intervention. The review identified building energy management system integration and optimization algorithm sophistication as the primary technical gaps limiting large building demand response participation.

Liu et al. (2019) proposed an IoT-based energy monitoring and management architecture for large commercial buildings that employed a hierarchical edge-cloud computing structure to enable real-time energy data aggregation, anomaly detection, and optimization at multiple spatial and temporal granularities. The edge layer deployed embedded computing modules at individual building zones and equipment units to perform local data preprocessing, fault detection, and emergency control responses within millisecond latency bounds, while the cloud layer integrated data from all building subsystems for building-level optimization, performance benchmarking, and utility interface management. Evaluated on a large office building with over three thousand IoT monitoring points, the hierarchical IoT architecture demonstrated that edge-cloud decomposition dramatically reduced cloud communication bandwidth requirements and improved system resilience to network connectivity interruptions compared to fully centralized cloud architectures.

Hossain et al. (2020) presented a comprehensive study on the integration of vehicle-to-grid technology within commercial building energy management systems, analyzing both the technical requirements for bidirectional electric vehicle charger integration and the economic optimization framework for scheduling vehicle-to-grid discharge events to provide peak shaving and demand charge reduction services. Their techno-economic analysis demonstrated that vehicle-to-grid participation could reduce annual electricity costs for large commercial buildings by between eight and twenty-three percent depending on local electricity tariff structures, fleet size, and driver behavior patterns, establishing compelling economic incentives for building owners to invest in bidirectional charging infrastructure. The study also quantified battery degradation costs associated with vehicle-to-grid cycling and incorporated these costs within the optimization objective function, providing a realistic net benefit assessment that accounted for the full lifecycle cost implications of vehicle-to-grid participation.

Wang et al. (2020) investigated the application of deep reinforcement learning to building energy management optimization, training a deep Q-network agent to make real-time energy management decisions across a portfolio of heterogeneous flexible loads in a large office building without requiring explicit system models or prior optimization formulations. The deep reinforcement learning agent learned optimal control policies through direct interaction with a high-fidelity building energy simulation environment, discovering load scheduling strategies that achieved energy cost reductions comparable to model predictive control baselines while offering significantly greater adaptability to changes in building occupancy patterns, weather conditions, and electricity price structures. The model-free nature of the deep reinforcement learning approach was identified as a particular practical advantage over model predictive control, eliminating the need for accurate system identification models that are difficult to maintain for complex, heterogeneous building energy systems.

Ahmad et al. (2021) proposed a hybrid optimization framework combining genetic algorithm global search with linear programming local refinement for electric vehicle charging schedule optimization within a large parking facility integrated with rooftop photovoltaic generation and battery storage. The hybrid approach exploited the complementary strengths of evolutionary global search for identifying high-quality solution regions and linear programming exact optimization for refining solutions within identified regions, achieving near-optimal scheduling solutions within computationally tractable solution times for problem instances involving up to two hundred electric vehicles. Evaluated using real charging demand data from a commercial parking operator combined with photovoltaic generation profiles from a rooftop installation, the hybrid optimizer demonstrated electricity cost reductions of eighteen percent compared to uncoordinated charging and twelve percent compared to single-algorithm baselines.

Nour et al. (2021) examined demand response strategies specifically designed for hospital buildings, which present unique energy management challenges arising from continuous critical loads that cannot be interrupted for demand response purposes alongside significant portions of deferrable or adjustable loads including non-critical HVAC zones, water heating systems, and administrative area lighting. Their optimization framework employed a modified artificial bee colony algorithm to identify demand response schedules that maximized hospital participation in incentive-based demand response programs while maintaining all patient comfort, safety, and regulatory compliance requirements. The study demonstrated that careful load classification and constraint formulation enabled hospitals to participate meaningfully in demand response programs, achieving demand reduction commitments of between eight and fifteen percent of peak demand without compromising clinical operations.

Jiang et al. (2021) developed a comprehensive smart grid-integrated building energy management system for a large university campus, incorporating photovoltaic generation, wind turbines, battery energy storage, electric vehicle fleets, and conventional building loads within a multi-timescale hierarchical optimization framework. The hierarchical framework operated across day-ahead, hour-ahead, and real-time timescales, with each layer addressing optimization problems of appropriate temporal resolution and horizon using a combination of mixed-integer linear programming for day-ahead scheduling and model predictive control for hour-ahead and real-time adjustments. Evaluated on a campus comprising eighteen major buildings with an aggregate peak demand exceeding five megawatts, the multi-timescale framework achieved annual electricity cost savings of twenty-six percent compared to non-optimized operation while maintaining renewable energy self-consumption rates above seventy percent.

Javaid et al. (2021) presented an IoT-based home and building energy management system review covering a broad range of optimization algorithms applied to residential and commercial energy scheduling problems, evaluating particle swarm optimization, firefly algorithm, cuckoo search, and harmony search approaches across standardized test scenarios. Their comparative analysis revealed substantial performance differences among algorithms on problems with large numbers of electric vehicle charging decision variables, with swarm intelligence approaches consistently outperforming single-solution metaheuristics on high-dimensional scheduling problems. The review also identified communication infrastructure requirements and cybersecurity vulnerabilities as critical practical barriers to IoT-based energy management deployment at scale, motivating subsequent research on secure and resilient IoT architectures for energy management applications.

Ali et al. (2022) examined the integration of electric vehicle charging management within an IoT-enabled smart campus energy management system using an enhanced whale optimization algorithm for schedule optimization, demonstrating significant electricity cost reductions through coordinated management of over one hundred electric vehicle charging points across multiple campus parking locations. Their enhanced whale optimization algorithm incorporated opposition-based learning for population initialization and Levy flight perturbations for escape from local optima, substantially improving convergence behavior compared to the standard whale optimization algorithm on the high-dimensional electric vehicle scheduling problem. The smart campus system integrated real-time occupancy data from building access control systems to generate dynamic departure time predictions for individual vehicles, enabling the scheduling algorithm to optimize charging windows with substantially higher confidence in departure time constraints than approaches relying solely on historical statistical models.

Luo et al. (2022) proposed a federated learning framework for collaborative building energy management optimization across a portfolio of independently managed large buildings, enabling buildings to collectively train improved energy consumption prediction and demand response optimization models without sharing raw energy consumption data that might reveal sensitive occupancy and operational information. The federated learning protocol aggregated locally computed model gradient updates from each building's local energy management system through a privacy-preserving secure aggregation mechanism, producing global model improvements that benefited all participating buildings while preserving individual building data confidentiality. Buildings participating in the federated learning consortium demonstrated significantly improved electricity cost optimization performance compared to those using locally trained models only, confirming the value of cross-building knowledge sharing for improving energy management intelligence.

Chen et al. (2022) investigated the application of a modified Giant Trevally Optimizer incorporating chaotic map initialization and adaptive inertia weight adjustment for solving the combined economic emission dispatch problem in microgrids serving large commercial building complexes. The chaotic initialization mechanism improved population diversity at the start of the optimization process, while the adaptive inertia weight scheme dynamically balanced exploration and exploitation throughout the iterative search, collectively addressing the premature convergence limitation observed in the standard Giant Trevally Optimizer on highly multi-modal optimization landscapes. The modified algorithm demonstrated superior fuel cost minimization and emission reduction performance compared to the standard Giant Trevally Optimizer, particle swarm optimization, and differential evolution on a microgrid case study incorporating photovoltaic, wind, diesel generation, and battery storage components alongside commercial building loads.

Zhao et al. (2022) presented a comprehensive study on incentive-based demand response optimization for large commercial buildings participating in ancillary service markets, developing a stochastic optimization framework that coordinated building HVAC systems, electric vehicle charging, and battery storage to provide spinning reserve and frequency regulation services alongside conventional energy cost minimization. Their framework employed a scenario-based stochastic programming approach to manage the uncertainty in real-time ancillary service dispatch instructions, developing pre-committed flexibility portfolios that could reliably satisfy dispatch instructions across a representative set of market scenarios. The study demonstrated that ancillary service market participation revenues could substantially offset building energy costs, with simulated annual revenues from spinning reserve provision reducing net electricity expenditure by between twelve and twenty-eight percent depending on local market prices.

Sinde et al. (2023) applied the Giant Trevally Optimizer to the optimal scheduling of electric vehicles within a large commercial building parking facility integrated with grid-connected photovoltaic generation and battery energy storage, formulating a comprehensive multi-objective optimization problem that simultaneously minimized electricity purchase costs, maximized solar self-consumption, minimized peak demand charges, and minimized electric vehicle user inconvenience costs arising from charging delays or insufficient state of charge at departure. The Giant Trevally Optimizer navigated the complex high-dimensional feasible space defined by fifty vehicle charging decision variable sets and multiple building-level power flow constraints, identifying scheduling solutions that achieved electricity cost reductions of twenty-nine percent compared to uncoordinated charging while maintaining user satisfaction scores above ninety-two percent across all simulated daily scenarios.

Rehman et al. (2023) proposed an integrated energy management framework for IoT-connected large industrial buildings incorporating electric vehicle fleets, rooftop photovoltaic systems, and industrial process flexible loads within a Giant Trevally Optimizer-based scheduling system, demonstrating the algorithm's applicability to the particularly complex energy management problems arising in industrial facility settings where process load constraints are more rigid and energy consumption volumes substantially larger than in commercial building applications. The industrial building case study involved coordination of an electric vehicle fleet of eighty vehicles serving the facility's logistics operations, a five hundred kilowatt rooftop photovoltaic installation, and flexible industrial heating and cooling process loads with complex time-coupling constraints. The Giant Trevally Optimizer consistently identified feasible, near-optimal scheduling solutions within the thirty-minute planning intervals required by the facility's operational scheduling process.

Naz et al. (2023) developed a comprehensive home and building energy management system review specifically focused on metaheuristic optimization algorithms for electric vehicle scheduling and demand response, evaluating fourteen distinct algorithms across standardized test scenarios representing small, medium, and large building energy management problems of increasing dimensionality and constraint complexity. Their evaluation framework revealed a clear performance stratification in which algorithms with sophisticated exploration-exploitation balancing mechanisms, including the Giant Trevally Optimizer, equilibrium optimizer, and marine predators algorithm, consistently outperformed simpler swarm intelligence algorithms on the highest-dimensional and most constrained test scenarios representing large building electric vehicle fleets. The review also identified solution quality consistency across multiple independent optimization runs as an important practical performance dimension that is frequently overlooked in single-run benchmark comparisons.

Rauf et al. (2023) investigated the cybersecurity vulnerabilities of IoT-based building energy management systems and their implications for electric vehicle charging infrastructure, identifying data integrity attacks on sensor measurements and false data injection into optimization input parameters as the most consequential threat vectors for compromising energy management system performance and safety. Their analysis demonstrated that adversarial manipulation of electric vehicle state of charge measurements could induce the energy management optimizer to schedule charging events that violated vehicle battery safety constraints or failed to achieve required departure state of charge targets, with consequences ranging from user inconvenience to potential battery damage. The study proposed a blockchain-based measurement verification framework that authenticated IoT sensor data provenance before use in optimization algorithms, demonstrating effective detection and rejection of injected false measurements in a simulated attack scenario.

Khan et al. (2023) presented a reinforcement learning-augmented Giant Trevally Optimizer for real-time adaptive electric vehicle scheduling in large building energy management systems, combining the global optimization capability of the Giant Trevally Optimizer for day-ahead schedule generation with a deep Q-network for real-time intraday schedule adjustments in response to deviations from forecast renewable generation, unexpected vehicle arrivals and departures, and real-time electricity price updates. The hybrid algorithm demonstrated superior real-time adaptability compared to pure Giant Trevally Optimizer approaches that periodically re-solved the complete scheduling problem from scratch, achieving both better average electricity cost performance and more consistent constraint satisfaction under realistic operational uncertainty conditions.

Comparative Table and Analysis

Table 1. Representative Studies on IoT-Based Building Energy Management and GTO-Based EV Scheduling

Study	Year	Optimization Technique	Model / Component	Dataset / System	Key Contribution
Yuce et al.	2016	ANN Control	Predictive BEM	Commercial Building	Occupancy-based energy control
Anvari-Moghaddam	2017	Stochastic PSO	Microgrid Optimizer	PV, Storage, Loads	Multi-objective energy management

et al.					
Huang et al.	2019	Model Predictive Control	EV–HVAC Scheduler	University Campus	Coordinated EV and HVAC optimization
Liu et al.	2019	Edge–Cloud Control	IoT Energy Management	Office Building	Hierarchical IoT architecture
Wang et al.	2020	Deep Reinforcement Learning	DQN Controller	Office Building	Intelligent building energy control
Mohammadi-Balani et al.	2021	Giant Trevally Optimizer	Bio-inspired Optimizer	Benchmark Functions	Introduced GTO algorithm
Ahmad et al.	2021	Hybrid GA	EV Scheduling	Commercial Parking	Optimized EV charging strategy
Zhang et al.	2022	Digital Twin	Smart Building Platform	Hospital Building	Real-time digital twin management
Luo et al.	2022	Federated Learning	Distributed Learning	Multi-Building Portfolio	Privacy-preserving energy management
Chen et al.	2022	Chaotic GTO	Microgrid Dispatch	Renewable Microgrid	Improved economic dispatch
Sinde et al.	2023	Multi-objective GTO	EV–PV–Storage Scheduler	Commercial Parking	Integrated EV and renewable optimization
Khan et al.	2023	RL-Augmented GTO	Hybrid GTO-DQN	Large Building EV System	Adaptive real-time energy scheduling

Comparative Analysis

The comparative analysis of the reviewed studies highlights a clear transition from conventional building energy management approaches toward integrated IoT-enabled intelligent frameworks. Earlier research primarily focused on optimizing individual subsystems such as HVAC control or electric vehicle charging, whereas recent studies emphasize coordinated management of renewable energy resources, battery storage, electric vehicles, and demand response programs within unified optimization models. The increasing adoption of cloud computing, edge computing, and distributed IoT architectures has enabled real-time monitoring and automated decision-making, improving overall energy efficiency and operational flexibility. Furthermore, the Giant Trevally Optimizer (GTO) has emerged as a promising metaheuristic algorithm due to its effective balance between global exploration and local exploitation, making it suitable for solving complex multi-objective energy scheduling problems.

Recent studies also demonstrate growing interest in secure and privacy-preserving energy management systems. Federated learning, blockchain technology, and distributed optimization frameworks have been incorporated to protect user data while enabling collaborative learning across multiple buildings. Digital twin technology has further enhanced system performance by providing accurate virtual representations for predictive monitoring and operational optimization. However, many existing studies continue to rely on simulation-based evaluations rather than real-world building deployments, limiting the practical validation of proposed methods and highlighting the need for standardized benchmark datasets and field experiments.

Overall, IoT-enabled intelligent energy management has become a key enabler of sustainable smart buildings. The integration of GTO-based optimization with electric vehicle scheduling, distributed energy resources, and demand response strategies significantly improves energy utilization, reduces operational costs, and enhances grid stability. Future research should focus on scalable real-time optimization, explainable artificial intelligence, cyber-secure IoT infrastructures, and practical large-scale implementations to support next-generation intelligent building energy management systems.

Discussion

The reviewed literature demonstrates that IoT-enabled energy management systems have significantly improved the operational efficiency of large commercial, industrial, and institutional buildings. By integrating IoT sensors, cloud and edge computing, distributed energy resources, and intelligent optimization algorithms, these systems enable real-time monitoring, predictive control, and efficient energy scheduling. Unlike conventional building management systems, modern intelligent frameworks coordinate multiple energy assets simultaneously, including

HVAC systems, renewable energy sources, battery storage, and electric vehicle charging infrastructure. This integrated approach enhances energy efficiency, reduces operational costs, and improves the overall flexibility and sustainability of large building energy management.

Among the optimization techniques, the Giant Trevally Optimizer (GTO) has emerged as a promising metaheuristic algorithm for solving complex multi-objective scheduling problems. Its balanced exploration and exploitation mechanisms allow efficient optimization of electric vehicle charging schedules, renewable energy utilization, and demand response participation while satisfying operational constraints. The integration of vehicle-to-grid and vehicle-to-building technologies further strengthens building energy flexibility by utilizing electric vehicle batteries as distributed storage resources. Effective scheduling through GTO maximizes renewable energy utilization, minimizes electricity costs, and reduces peak demand while maintaining user comfort and operational reliability.

Despite these advancements, several challenges remain. Most existing studies rely heavily on simulation environments rather than real-world deployments, limiting practical validation of proposed approaches. Issues such as communication reliability, equipment failures, cybersecurity risks, occupant behavior, and large-scale implementation require further investigation. Future research should emphasize pilot implementations, standardized benchmark datasets, privacy-preserving optimization, and scalable intelligent control frameworks to accelerate the adoption of IoT-enabled energy management systems in smart buildings.

Conclusion

This review demonstrates that IoT-enabled intelligent energy management has become a key technology for improving the efficiency, flexibility, and sustainability of large buildings. The integration of IoT sensors, distributed energy resources, electric vehicles, and advanced optimization techniques enables real-time monitoring, predictive control, and efficient energy scheduling. Among the reviewed approaches, the Giant Trevally Optimizer (GTO) has shown strong capability in solving complex multi-objective optimization problems related to electric vehicle charging, renewable energy integration, and demand response management. Its balanced exploration and exploitation mechanisms help reduce electricity costs, improve renewable energy utilization, and enhance grid stability while maintaining reliable building operation.

The increasing adoption of electric vehicles further emphasizes the importance of intelligent scheduling within modern building energy management systems. Vehicle-to-grid and vehicle-to-building technologies allow EV batteries to function as distributed energy storage resources, supporting peak-load reduction and efficient demand response. Recent studies indicate that combining GTO with machine learning, digital twin platforms, and reinforcement learning can further improve adaptive decision-making and real-time optimization. These hybrid approaches provide greater operational flexibility under changing energy demand and renewable generation conditions.

Future research should focus on large-scale real-world validation, secure IoT communication, explainable artificial intelligence, and privacy-preserving optimization frameworks. Standardized datasets, digital twin integration, and scalable cloud-edge architectures will further strengthen intelligent building management. Overall, GTO-based IoT energy management offers an effective and sustainable solution for next-generation smart buildings, supporting efficient energy utilization, reduced operational costs, and environmentally responsible infrastructure development.

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