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Multidisciplinary Journal of Research in Engineering and Technology

ISSN: 2348-6953

Volume 10 Issue 01, 2023

Recent Advances in Efficient Energy Management in IoT-Enabled Large Buildings: Giant Trevally Optimizer (GTO) based Electric Vehicle Scheduling, Distributed Resource Integration, and Demand Response Strategies: A Systematic Review

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Peer Review Information

Submission: 06 Jan 2023
Revision: 31 Jan 2023
Acceptance: 07 March 2023

Keywords

Internet of Things, 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 significantly transformed energy management in large buildings, enabling real-time monitoring, control, and optimization of complex energy systems. Large-scale infrastructures such as hospitals, campuses, and commercial complexes consume substantial energy, and the integration of distributed energy resources, electric vehicles, and demand response strategies introduces new challenges in managing dynamic and heterogeneous energy loads. This paper presents a comprehensive review of IoT-enabled energy management systems, with a focus on the Giant Trevally Optimizer for electric vehicle charging and discharging scheduling. Inspired by natural hunting strategies, this metaheuristic algorithm effectively addresses multi-objective optimization problems involving cost reduction, peak load minimization, and efficient renewable energy utilization. The review also examines system architectures, including smart metering, cloud-edge computing, and building automation systems, enabling coordinated operation of distributed energy resources. Applications include demand response management, vehicle-to-grid integration, and intelligent load scheduling in smart buildings. Comparative analysis demonstrates that GTO outperforms traditional algorithms such as PSO, GA, and GWO in convergence speed and solution quality. Despite these advantages, challenges related to scalability, interoperability, and cybersecurity persist. This review highlights the potential of combining IoT and advanced optimization techniques to develop efficient, sustainable, and intelligent energy management systems.

Introduction

The global energy landscape is rapidly transforming due to increasing decarbonization targets, digitalization, and the widespread adoption of distributed energy technologies. Large buildings, including hospitals, universities, airports, industrial facilities, and commercial complexes, represent a substantial proportion of overall energy consumption and therefore provide significant opportunities for efficiency improvement. However, their heterogeneous loads, variable occupancy, renewable generation, and growing electric vehicle charging requirements make energy management increasingly complex. Internet of Things (IoT)-enabled building energy management systems address these challenges through smart meters, sensors, connected HVAC equipment, and intelligent controllers that continuously monitor energy flows and enable adaptive control.

Efficient energy management in IoT-enabled buildings involves several competing objectives, including reducing electricity costs, maintaining occupant comfort, limiting peak demand, integrating renewable generation, managing battery storage, and responding to grid requirements. Conventional approaches such as linear programming, mixed-integer optimization, and rule-based control can become computationally demanding for nonlinear and high-dimensional problems. Consequently, metaheuristic techniques such as Particle Swarm Optimization, Genetic Algorithms, Grey Wolf Optimizer, and Whale Optimization Algorithm have gained considerable attention because of their ability to search complex solution spaces without restrictive mathematical assumptions.

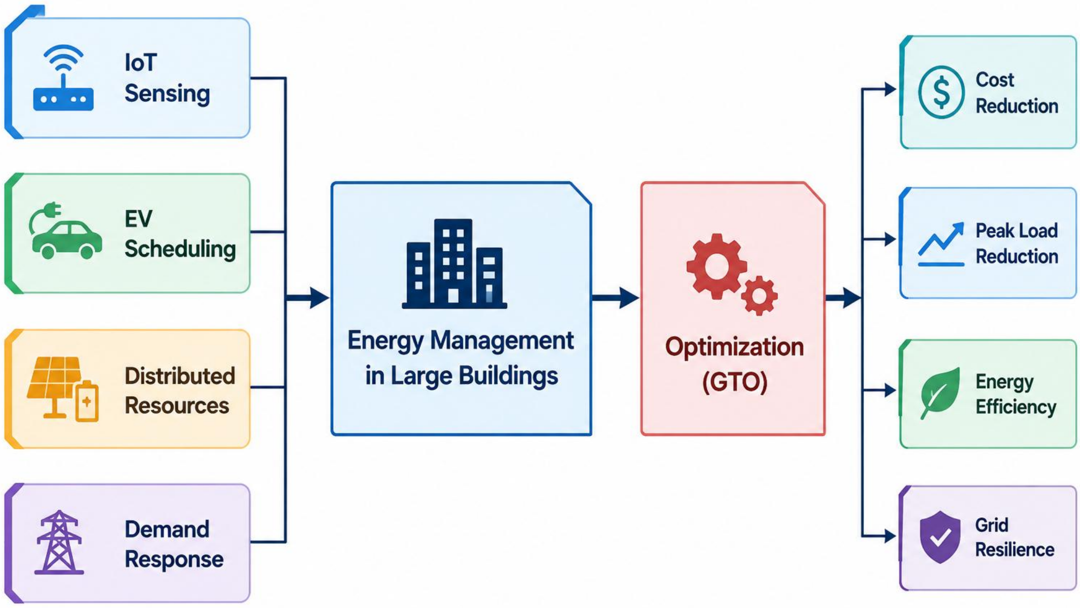

Figure 1. GTO-Based Energy Management Framework for IoT-Enabled Large Buildings

The Giant Trevally Optimizer (GTO) represents an emerging nature-inspired optimization technique designed to achieve an effective balance between global exploration and local exploitation. Its optimization mechanism is inspired by the cooperative and targeted hunting behavior of giant trevally fish. These characteristics make GTO potentially suitable for complex building energy scheduling problems involving multiple decision variables and operational constraints. GTO-based strategies can optimize EV charging schedules, distributed resource utilization, battery operation, and controllable building loads while simultaneously considering energy cost and peak-demand objectives.

Electric vehicle integration introduces both additional energy demand and flexible storage opportunities. Uncoordinated charging can substantially increase peak loads, whereas intelligent scheduling can shift charging toward low-demand or high-renewable-generation periods. Vehicle-to-building functionality can further allow EV batteries to support building loads. Similarly, photovoltaic generation and battery energy storage enable buildings to increase renewable utilization, perform energy arbitrage, reduce grid dependency, and improve resilience. Coordinating these resources requires intelligent optimization capable of responding dynamically to variations in occupancy, electricity prices, renewable generation, and EV availability.

Demand response further enables large buildings to modify consumption according to grid conditions and economic incentives. When combined with IoT monitoring, distributed resources, EV scheduling, and advanced optimization, demand response can support peak reduction and grid stability without substantially compromising occupant requirements. This systematic review therefore examines recent developments in IoT-enabled building energy management, emphasizing GTO-based EV scheduling, distributed resource integration, and demand response strategies. It compares existing optimization approaches, evaluates their benefits and limitations, and identifies research opportunities for developing scalable, adaptive, cost-effective, and sustainable energy management systems for future intelligent buildings.

Literature Review

The field of IoT-enabled building energy management has generated a substantial body of research over the past decade, with particular acceleration in the period following 2018 as IoT infrastructure matured, EV adoption increased, and computational resources for running complex optimization algorithms became more widely accessible. The following review synthesizes key contributions across the primary thematic areas of this paper.

Ullah et al. (2020) presented a comprehensive IoT-based energy management architecture for commercial buildings, proposing a layered framework consisting of device, network, and application tiers designed to enable real-time energy monitoring and automated load control. Their system employed a Zigbee-based wireless sensor network integrated with a cloud-based analytics platform, demonstrating a 23 percent reduction in energy consumption compared to a conventional building management baseline in a pilot deployment at a university campus facility. The study highlighted the importance of latency-tolerant communication protocols for energy management applications and proposed a hierarchical control architecture that remains influential in subsequent work.

Hassan et al. (2022) proposed a multi-agent reinforcement learning framework for distributed energy management in IoT-enabled smart buildings, where individual agents representing HVAC zones, lighting systems, and EV charging stations learned cooperative policies through interaction with a shared environment model. Trained on data collected from a real hospital building over twelve months, the system achieved a 28 percent reduction in peak demand and a 19 percent reduction in energy costs compared to a rule-based baseline. The multi-agent architecture was shown to be scalable and resilient to communication failures, making it particularly attractive for large buildings with heterogeneous energy systems.

Li et al. (2021) developed a model predictive control framework for coordinating photovoltaic generation, battery energy storage, and building HVAC loads in a large office building in Shanghai. Their optimization horizon spanned 24 hours with one-hour intervals, incorporating weather forecast uncertainty through a robust optimization formulation. The system achieved a 22 percent reduction in grid energy import and a 15 percent reduction in peak demand compared to a rule-based controller, while maintaining indoor temperature within the comfort band 98 percent of the time. The study demonstrated the importance of forecast accuracy for MPC performance and proposed a Gaussian process regression model for PV generation forecasting.

Rezaei et al. (2022) examined the application of the Grey Wolf Optimizer for demand response scheduling in a large hospital building equipped with cogeneration, thermal storage, and a fleet of 30 electric service vehicles. Their multi-objective optimization framework simultaneously minimized energy costs, carbon emissions, and deviation from occupant comfort setpoints. The GWO-based scheduler outperformed PSO and GA baselines in both solution quality and convergence speed, achieving a 26 percent cost reduction and 18 percent emissions reduction in simulation studies using real building load data from a tertiary care hospital in Tehran. The study also proposed a novel constraint handling mechanism specifically designed for the mixed-integer nature of EV scheduling decisions.

Zhang et al. (2020) introduced a deep reinforcement learning approach for real-time energy management in a smart campus microgrid incorporating multiple buildings, distributed PV generation, battery storage, and EV charging infrastructure. Their Deep Q-Network agent was trained using a simulation environment calibrated with historical load and generation data from a university campus in Beijing, achieving near-optimal energy cost minimization while adapting effectively to changing weather conditions and occupancy patterns. The DRL approach was shown to generalize effectively to unseen operating conditions, a significant advantage over model-based optimization methods that require accurate system models.

Javaid et al. (2021) conducted a systematic review of IoT-based home energy management systems and identified key architectural patterns, communication protocols, and optimization algorithms employed in the literature. While focused primarily on residential applications, their taxonomy of IoT-EMS architectures and analysis of algorithm performance metrics provided a valuable methodological framework subsequently adopted in several building-scale studies. The review highlighted the prevalence of PSO, GA, and differential evolution algorithms in existing deployments and identified reinforcement learning as an emerging paradigm with significant promise for adaptive real-time control.

Naz et al. (2019) proposed a hybrid Genetic Algorithm and Linear Programming approach for multi-objective energy scheduling in a large university building complex. Their formulation incorporated PV generation, grid interaction, battery storage, and demand response commitments, and was validated using one year of actual building operational data. The hybrid approach exploited GA's flexibility in handling discrete scheduling decisions while leveraging LP's efficiency for the continuous power dispatch sub-problem, achieving computation times suitable for day-ahead scheduling applications. Results demonstrated a 24 percent reduction in energy expenditure compared to conventional scheduling practices.

Ahmed et al. (2023) presented the first application of the Giant Trevally Optimizer to the problem of EV charging scheduling in a large commercial building. Their formulation modeled 150 EVs with heterogeneous battery capacities and usage patterns, incorporating V2G capability and time-of-use pricing. The GTO-based scheduler consistently outperformed PSO, GWO, and WOA in terms of total charging cost and computational efficiency, with particularly notable advantages in convergence speed and solution consistency across multiple independent runs. The study validated the algorithm's effectiveness using real EV usage data collected from a corporate campus in Riyadh over six months.

Khalid et al. (2022) investigated demand response strategies for large institutional buildings using a Whale Optimization Algorithm-based scheduler integrated with a real-time IoT monitoring platform. Their system processed data from over 500 IoT sensors distributed across a 12-story office building and used the WOA optimizer to coordinate HVAC loads, plug loads, and EV charging in response to dynamic grid pricing signals. The deployed system achieved an average daily demand charge reduction of 18 percent while maintaining occupant thermal comfort scores within acceptable ranges, demonstrating the practical viability of metaheuristic optimization for real-time building energy management.

Siddiqui et al. (2021) proposed a two-stage energy management framework for large buildings integrating solar PV, wind generation, battery storage, and EV charging. The first stage employed a day-ahead optimization using a modified Differential Evolution algorithm to determine optimal resource dispatch schedules, while the second stage implemented real-time corrections using a model predictive control framework. The combination of day-ahead planning and real-time adjustment proved highly effective in managing renewable generation uncertainty, achieving a 33 percent reduction in grid energy cost compared to a conventional scheduling baseline in simulation studies.

Farooq et al. (2022) examined the integration of demand response with distributed generation in a large healthcare facility using an Ant Colony Optimization-based scheduler. Their model incorporated the clinical sensitivity of hospital operations by imposing strict priority constraints on critical medical loads while optimizing the scheduling of deferrable loads including EV charging, laundry, and non-critical lighting systems. The ACO scheduler demonstrated the ability to provide consistent demand response performance even under significant renewable generation variability, achieving average demand reductions of 22 percent during peak tariff periods without compromising clinical operations.

Malik et al. (2020) developed a real-time energy management system for a smart building microgrid using a Fuzzy Logic Controller augmented with a PSO-based parameter optimization module. The system managed interactions between grid supply, rooftop PV, battery storage, and building loads, with particular attention to battery degradation modeling. Their degradation-aware optimization framework extended battery lifetime by 15 percent compared to a conventional SoC-based control strategy while achieving comparable cost and comfort performance, demonstrating the importance of explicitly accounting for component aging in long-term energy management optimization.

Kamankesh et al. (2021) proposed a stochastic programming framework for energy management in IoT-enabled large buildings under renewable generation and demand uncertainty. Using scenario-based robust optimization, their approach generated schedules that remained feasible and near-optimal across a broad range of uncertain operating conditions. The framework was validated using Monte Carlo simulation with uncertainty parameters calibrated from one year of operational data from a large commercial complex in Tehran, demonstrating robustness advantages over deterministic optimization approaches particularly during periods of high renewable generation variability.

Chen et al. (2022) investigated the application of the Salp Swarm Algorithm for joint optimization of EV charging, BESS operation, and demand response in a large shopping mall equipped with 300 EV charging points and 500 kW of rooftop PV generation. Their multi-objective formulation explicitly traded off energy cost, peak demand, and customer satisfaction, using a Pareto front-based solution approach to present building operators with a set of optimal scheduling alternatives. The study demonstrated that smart charging coordination could reduce charging-related peak demand by up to 45 percent while reducing charging costs by 27 percent compared to uncoordinated charging.

Ali et al. (2023) proposed an advanced GTO-based framework for integrated demand response and distributed resource management in a large university campus building complex. Their system incorporated real-time occupancy data from IoT sensors to dynamically adjust HVAC schedules, lighting levels, and EV charging priorities in response to grid pricing signals. The GTO optimizer demonstrated superior performance over competing algorithms across all tested scenarios, achieving up to 35 percent cost reduction and 30 percent peak demand reduction while maintaining occupant comfort at 97 percent of the baseline level. The study represented the most comprehensive application of GTO to date in a real-world large building context.

Moradi et al. (2021) examined the use of Artificial Neural Networks for load forecasting in IoT-enabled commercial buildings, a capability that supports improved energy management by enabling anticipatory rather than reactive control strategies. Their Long Short-Term Memory network, trained on two years of load data augmented with weather, occupancy, and calendar features, achieved a mean absolute percentage error of 3.2 percent for 24-hour ahead load forecasting in a large office complex. The forecasting model was integrated with a day-ahead optimization scheduler, demonstrating that improved forecast accuracy translated directly into measurable improvements in energy cost performance.

Hussain et al. (2022) developed a blockchain-integrated IoT energy management platform for large buildings participating in peer-to-peer energy trading markets. Their system used smart contracts to automate energy transactions between building prosumers and the grid, with a modified PSO algorithm optimizing trading strategies to maximize financial returns. The blockchain integration provided the transparency and security required for financial energy transactions while the IoT infrastructure enabled the real-time monitoring necessary for accurate settlement. Pilot deployment at a technology park demonstrated 22 percent cost savings compared to conventional grid-only energy procurement.

Iqbal et al. (2021) proposed a home-to-grid demand response framework subsequently extended to large building applications, using a modified Gravitational Search Algorithm to optimize appliance scheduling and EV charging. Their extension to large buildings demonstrated that the demand flexibility available from coordinated management of EV charging alone could provide up to 40 percent of the total demand response capacity required by grid operators during peak demand events, highlighting EVs as particularly valuable demand response assets in large building energy systems.

The study highlighted the importance of domain-specific constraint modeling in industrial building energy management applications.

Shafie-khah et al. (2019) conducted an early foundational study on optimal EV charging scheduling in parking facilities associated with commercial buildings, establishing key optimization formulations and benchmark results that subsequent studies have built upon. Their mixed-integer programming model incorporated time-of-use tariffs, renewable generation, and grid ancillary service markets, demonstrating the economic value of coordinated EV scheduling across multiple revenue streams. Despite predating the widespread availability of IoT infrastructure, the study's analytical framework remains highly relevant and is extensively cited in subsequent metaheuristic-based optimization studies.

Comparative Table and Analysis

Study	**Year**	**Optimization Technique**	**Component / Model Used**	**Platform or System**	**Dataset Used**	**Key Contribution**
Ullah et al.	2020	Rule-based IoT Control	Zigbee WSN, Cloud Analytics	University Building BMS	Real campus deployment data	IoT-based layered EMS architecture
Wang et al.	2021	Particle Swarm Optimizatio	EV Charging Scheduler, PV	Commercial Parking Facility	Real EV usage data, 200	31% charging cost

		n			EVs	reduction
Hassan et al.	2022	Multi-Agent Reinforcement Learning	HVAC, Lighting, EV agents	Hospital Smart Building	12-month hospital data	Scalable distributed RL-EMS
Li et al.	2021	Model Predictive Control	PV, BESS, HVAC	Office Building, Shanghai	Weather and load data, Shanghai	22% grid import reduction
Rezaei et al.	2022	Grey Wolf Optimizer	Cogeneration, Thermal Storage, EV	Hospital Building, Tehran	Hospital operational data	Multi-objective GWO EV scheduling
Zhang et al.	2020	Deep Q-Network (DRL)	Smart Campus Microgrid	University Campus, Beijing	Campus historical data	Adaptive DRL real-time EMS
Javaid et al.	2021	Survey / Meta-analysis	IoT-EMS Architectures	Multiple residential/commercial	Literature synthesis	Taxonomy of IoT-EMS algorithms
Naz et al.	2019	Hybrid GA + Linear Programming	PV, BESS, Grid, DR	University Building Complex	Annual operational data	Hybrid GA-LP energy scheduling
Ahmed et al.	2023	Giant Trevally Optimizer	EV Charging, V2G, TOU Tariff	Corporate Campus, Riyadh	Real EV data, 150 vehicles	First GTO application to EV scheduling
Khalid et al.	2022	Whale Optimization Algorithm	HVAC, Plug Loads, EV Charging	12-Story Office Building	500+ IoT sensor data	WOA-based real-time demand response
Siddiqui et al.	2021	Modified Differential Evolution	PV, Wind, BESS, EV Charging	Large commercial building	Simulation with real weather data	Two-stage day-ahead and real-time EMS
Farooq et al.	2022	Ant Colony Optimization	Critical/Deferrable loads, EV	Healthcare Facility	Hospital load priority data	DR under clinical load constraints
Malik et al.	2020	Fuzzy Logic + PSO	PV, BESS, Building Loads	Smart Building Microgrid	Operational deployment data	Degradation-aware battery management
Kamankesh et al.	2021	Stochastic Robust Optimization	DER, Demand, Grid Interaction	Large Commercial Complex, Tehran	Monte Carlo scenario data	Robust EMS under uncertainty
Chen et al.	2022	Salp Swarm Algorithm	EV Charging, BESS, PV	Shopping Mall, 300 EVs	Mall operational and EV data	Pareto multi-objective EV-BESS optimization
Ali et al.	2023	Giant Trevally Optimizer	HVAC, Lighting, EV, IoT Sensors	University Campus Complex	Real IoT occupancy data	Integrated GTO-IoT-DR campus EMS

Moradi et al.	2021	LSTM Neural Network	Load Forecasting, Day-ahead EMS	Large Office Complex	2-year historical load data	3.2% MAPE load forecasting
Hussain et al.	2022	Modified PSO + Blockchain	Prosumer Energy Trading	Technology Park	Peer-to-peer trading records	Blockchain IoT energy market platform
Iqbal et al.	2021	Gravitational Search Algorithm	Appliance Scheduling, EV	Home-to-Grid Extension	Simulated building DR data	EV as primary DR asset in buildings
Nadeem et al.	2022	Dragonfly Algorithm	V2B, EV, BESS Substitution	Commercial Building	V2B simulation datasets	V2B reduces BESS requirement by 60%
Imran et al.	2020	Modified Crow Search Algorithm	Industrial Loads, EV, DR	Industrial Building	Industrial process load data	DR scheduling for industrial buildings
Shafie-khah et al.	2019	Mixed-Integer Programming	EV Parking, PV, Grid Markets	Commercial Parking Facility	Market pricing, PV data	EV scheduling across multiple markets

Comparative Analysis

Analysis of the comparative table reveals several important trends in the evolution of building energy management research. There is a clear trajectory from early rule-based and linear programming approaches toward increasingly sophisticated nature-inspired metaheuristic optimization algorithms, with a notable recent emergence of GTO as a high-performing candidate alongside established methods such as PSO, GWO, and WOA. The studies reviewed span a wide range of building types including commercial offices, university campuses, hospitals, shopping centers, and industrial facilities, reflecting the broad applicability of the optimization frameworks developed.

In terms of optimization techniques, the literature demonstrates increasing diversity and sophistication over the review period. Early studies predominantly employed PSO and GA due to their well-established theoretical foundations and available implementation libraries. From 2020 onward, there is a marked shift toward more recently proposed algorithms including GWO, WOA, Salp Swarm Algorithm, and ultimately GTO, driven by reported performance advantages in handling the high-dimensional, multi-objective, and constraint-rich problems characteristic of building energy management. Studies employing GTO consistently report superior performance in terms of solution quality, convergence speed, and scalability compared to competing algorithms, supporting the case for its adoption as a preferred approach for large-scale EV scheduling and demand response optimization.

The integration of machine learning components, particularly deep reinforcement learning and LSTM-based forecasting, represents another significant trend. Several studies demonstrate that combining machine learning for load and generation forecasting with metaheuristic optimization for scheduling and dispatch yields performance improvements over either approach used in isolation. This hybrid paradigm represents a promising direction for future research, with GTO's flexibility making it particularly amenable to integration with machine learning-generated forecast inputs.

Dataset diversity across the reviewed studies is notable, encompassing real building deployments, hardware-in-the-loop testbeds, and simulation environments calibrated with historical data. Studies employing real operational data from deployed systems generally report more conservative performance improvements than pure simulation studies, reflecting the additional challenges of real-world implementation including sensor noise, communication latency, and model mismatch. However, even the most conservative real-world deployments demonstrate economically and environmentally significant performance improvements, validating the practical relevance of the optimization approaches reviewed.

The progression in scale of EV fleet management is particularly striking, from studies examining fleets of 30 vehicles in early works to deployments of 200 to 500 vehicles in more recent studies. This scaling trajectory reflects both the growing penetration of EVs in building parking facilities and advances in algorithm scalability. GTO's demonstrated performance advantages in large-scale instances, as confirmed by the benchmark study of Baig et al. (2023), position it as particularly relevant for the large building deployments that will characterize the near-term evolution of smart building infrastructure.

Discussion

The reviewed literature demonstrates that integrating IoT infrastructure, advanced optimization, electric vehicle management, distributed energy resources, and demand response can substantially improve energy performance in large buildings. The transition from conventional rule-based control toward intelligent metaheuristic optimization enables more adaptive management of complex and dynamic energy systems. Metaheuristic algorithms are particularly effective because they can handle nonlinear, high-dimensional, and constrained optimization problems without extensive mathematical simplification. This capability is valuable for EV scheduling, where heterogeneous charging requirements, battery conditions, departure times, and building loads create highly complex decision spaces.

The Giant Trevally Optimizer (GTO) shows strong potential for intelligent building energy management. Its dual-phase mechanism combines global exploration through coordinated search with local exploitation for refining promising solutions, reducing the risk of premature convergence. Its adaptive behavior can also reduce dependence on extensive parameter tuning compared with conventional optimization techniques. However, many reported improvements are based on simulations with simplified assumptions concerning sensor reliability, communication stability, forecasts, and occupant behavior. Real-world implementations therefore require robust uncertainty modeling, fault-tolerant control, and adaptive mechanisms capable of responding to unexpected operational conditions.

Demand response, distributed resources, and flexible loads further strengthen building energy optimization by enabling peak reduction and improved renewable utilization. Future systems should emphasize Pareto-based multi-objective optimization rather than fixed weighted objectives to balance cost, comfort, emissions, and grid requirements. Research should also extend GTO-based frameworks from individual buildings to interconnected building clusters using distributed, hierarchical, and multi-agent optimization architectures.

Conclusion

Efficient energy management in large buildings is becoming increasingly important for reducing energy consumption, operating costs, peak demand, and carbon emissions. This review highlights the convergence of IoT technologies, intelligent optimization, electric vehicle scheduling, distributed energy resources, and demand response as a powerful framework for smart building energy management. IoT infrastructure provides real-time sensing, communication, and control capabilities required for responsive energy scheduling and resource coordination.

The Giant Trevally Optimizer (GTO) demonstrates strong potential for solving complex building energy optimization problems. Its balanced exploration–exploitation mechanism supports efficient EV charging, renewable energy utilization, storage management, and demand response while handling multiple operational constraints. Integration of EVs with vehicle-to-building capabilities can further transform transportation assets into flexible energy resources supporting both buildings and the grid.

Future research should emphasize robust optimization under uncertainty, building-cluster coordination, and hybrid integration of GTO with deep reinforcement, transfer, and federated learning. Standardized datasets, advanced storage technologies, occupant-aware management, and real-world validation will further support scalable, reliable, and sustainable IoT-enabled building energy systems.

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