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**A Survey of Methods and Architectures for Efficient Energy Management in IoT-Enabled Large Buildings: Giant Trevally Optimizer (GTO) based Electric Vehicle Scheduling, Distributed Resource Integration, and Demand Response Strategies**

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Peer Review Information	Abstract
<p><i>Submission: 13 April 2025</i> <i>Revision: 30 April 2025</i> <i>Acceptance: 15 May 2025</i></p>	<p>The rapid integration of Internet of Things (IoT) technologies into large-scale buildings has significantly transformed building energy management systems by enabling real-time monitoring, control, and optimization. As buildings account for a major share of global energy consumption and emissions, the increasing integration of electric vehicles, distributed energy resources, and demand response mechanisms introduces complex, dynamic, and multi-objective optimization challenges that require advanced intelligent solutions. This paper presents a comprehensive review of IoT-enabled energy management frameworks, with a focus on the Giant Trevally Optimizer (GTO) for optimizing electric vehicle scheduling, distributed energy resource coordination, and demand response strategies. Inspired by natural predatory behavior, GTO provides an effective balance between exploration and exploitation, enabling efficient handling of high-dimensional and nonlinear optimization problems. The review also examines system architectures, including IoT sensing networks, edge-cloud computing, and machine learning-based forecasting for real-time decision-making. Applications include vehicle-to-grid integration, renewable energy management, and intelligent load scheduling in smart buildings. Comparative studies show that GTO-based and hybrid AI frameworks outperform traditional optimization methods in cost reduction, peak demand management, and renewable utilization. However, challenges such as scalability, cybersecurity, interoperability, and real-world deployment remain. This review highlights the potential of integrating IoT, AI, and advanced optimization techniques to develop efficient, scalable, and sustainable energy management systems for future smart buildings.</p>
<p><b>Keywords</b></p> <p><i>Internet of Things, Building Energy Management Systems, Giant Trevally Optimizer, Electric Vehicle Scheduling, Demand Response, Distributed Energy Resources, Metaheuristic Optimization</i></p>	

**Introduction**

The global energy system is undergoing a transformation of historic scale, driven by climate change mitigation goals, rapid digitalization, and the electrification of transportation, heating, and industrial processes.

Within this transition, buildings occupy a critical position, accounting for nearly 40% of global energy consumption and a significant share of carbon emissions. Large commercial and institutional buildings—including offices, hospitals, campuses, and shopping complexes—

offer substantial opportunities for energy optimization due to their scale and diversity of loads. Their complex infrastructure enables the deployment of advanced energy management strategies that can significantly enhance efficiency, reduce emissions, and improve operational flexibility.

The Internet of Things (IoT) has emerged as a key enabler of intelligent energy management in modern buildings. IoT-based systems integrate networks of sensors, smart meters, and actuators that continuously monitor environmental conditions, occupancy patterns, and equipment performance. These systems generate high-resolution data streams that provide unprecedented visibility into building operations. When combined with machine learning and optimization algorithms, IoT platforms enable predictive analytics and adaptive control, allowing building systems such as HVAC, lighting, and electric vehicle charging to respond dynamically to changing conditions and optimization objectives.

The increasing integration of distributed energy resources has further complicated building energy management. Technologies such as rooftop solar panels, battery storage systems, and electric vehicles transform buildings into active energy participants rather than passive consumers. These resources introduce variability and uncertainty, requiring sophisticated coordination to balance generation, storage, and consumption. Demand response programs add another layer of complexity by incentivizing buildings to adjust their energy usage based on grid conditions. Managing these interconnected systems in real time necessitates advanced optimization techniques capable of handling multi-objective and highly dynamic scenarios.

Traditional energy management approaches, including rule-based control and classical optimization methods, are often inadequate for addressing these challenges. Rule-based systems lack adaptability, while conventional optimization techniques struggle with non-linear, high-dimensional problems. In contrast, metaheuristic algorithms have gained prominence due to their flexibility and robustness. Among these, the Giant Trevally Optimizer (GTO) represents a recent advancement, offering efficient search capabilities inspired by natural behaviors. GTO is particularly well-suited for complex energy management tasks, including electric vehicle scheduling, renewable energy integration, and demand response coordination.

Electric vehicle scheduling has emerged as a critical application area within building energy

management. Uncoordinated EV charging can significantly increase peak demand, whereas optimized scheduling can enhance load balancing and renewable energy utilization. Similarly, integrating distributed energy resources requires careful consideration of uncertainty, storage constraints, and system reliability. Demand response strategies further demand accurate forecasting and rapid decision-making. By leveraging IoT data, artificial intelligence, and advanced optimization techniques such as GTO, modern building energy management systems can achieve enhanced efficiency, resilience, and sustainability, paving the way for smarter and more adaptive energy ecosystems.

### Literature Review

Shareef et al. (2018) presented one of the foundational works in the domain of IoT-enabled smart building energy management systems, establishing architectural principles that have since been widely adopted in subsequent research. Their study implemented a large-scale wireless sensor network comprising more than three hundred heterogeneous sensing nodes deployed across a university campus building environment. These sensors continuously monitored environmental variables, occupancy patterns, and energy usage profiles, transmitting real-time data streams to a centralized cloud-based analytics platform. The platform incorporated a neural network-based load forecasting engine alongside an automated control interface capable of managing HVAC systems, lighting infrastructure, and plug loads. The forecasting model achieved a high predictive accuracy of 94.3% for one-hour-ahead load estimation, demonstrating the effectiveness of deep learning in short-term energy prediction tasks. Based on these forecasts, the system executed proactive control strategies that resulted in a 17% reduction in peak demand and a 12% reduction in total energy consumption over a six-month operational period. This work significantly contributed to establishing real-time IoT data integration as a core requirement for intelligent building energy management systems.

Building upon predictive and IoT-driven frameworks, Li et al. (2019) introduced a deep reinforcement learning-based approach for optimal energy scheduling in commercial buildings equipped with distributed energy resources. Their model employed a deep Q-network (DQN) agent formulated as a Markov decision process, where system states included battery state-of-charge, photovoltaic generation levels, building load demand, and dynamic

electricity pricing signals. The action space consisted of decisions related to battery charging and discharging, as well as flexible load scheduling strategies. Using the EnerNOC dataset for training and validation, the model demonstrated strong adaptability across seasonal variations and tariff fluctuations. Experimental results over a twelve-month period showed a 22% reduction in electricity procurement costs compared to traditional rule-based methods, highlighting the capability of reinforcement learning systems to autonomously optimize building energy consumption without explicit reprogramming. Extending the reinforcement learning paradigm to distributed environments, Wang et al. (2020) proposed a cooperative multi-agent reinforcement learning framework for energy management in commercial building microgrids. In this architecture, individual agents were assigned to distinct energy assets, including rooftop photovoltaic systems, battery storage units, diesel generators, and electric vehicle charging stations. These agents operated collaboratively using a shared reward function designed to minimize energy costs while maximizing renewable energy utilization. Evaluated using real operational data from a large shopping mall in Shanghai, the proposed system achieved a 19.3% reduction in grid energy costs, an 11.8% increase in renewable self-consumption, and an 8.4% reduction in peak load demand. The study demonstrated the scalability and effectiveness of decentralized reinforcement learning in managing complex multi-resource energy systems. Zhang et al. (2020) explored the application of the Grey Wolf Optimizer (GWO) for demand response scheduling in IoT-enabled office buildings. The problem was formulated as a constrained optimization model aimed at minimizing electricity costs and occupant discomfort under dynamic pricing and environmental conditions. The system integrated real-time IoT-based occupancy data, smart meter readings, and weather forecasts to generate adaptive control strategies for HVAC and lighting systems. Using a calibrated EnergyPlus simulation model of a fifteen-story office building, the proposed GWO-based scheduler achieved a 24% reduction in demand response costs compared to genetic algorithm approaches, while also reducing computational complexity by requiring fewer function evaluations. This study highlighted the effectiveness of nature-inspired optimization techniques in building energy applications. Fang et al. (2021) addressed electric vehicle (EV) charging management in healthcare facilities

through a predictive model-based control framework. Their approach combined long short-term memory (LSTM) neural networks with model predictive control (MPC) to forecast EV arrival times and initial state-of-charge levels. The model was trained on eighteen months of real-world hospital EV charging data, capturing complex temporal usage patterns associated with staff, physicians, and visitors. The integrated system enabled efficient pre-scheduling of charging loads, reducing peak demand by 31% and eliminating demand charge violations. The study demonstrated the critical importance of accurate EV behavioral forecasting in optimizing building-level charging infrastructure.

Chen et al. (2021) addressed privacy concerns in multi-building energy forecasting through a federated learning framework. Their approach enabled decentralized model training across multiple commercial buildings without sharing raw energy data. Instead, only gradient updates were exchanged between local building systems and a global aggregation server. Evaluated on the ASHRAE Great Energy Predictor III dataset, the federated model achieved a mean absolute percentage error of 3.8%, comparable to centralized learning methods. Importantly, the framework incorporated differential privacy mechanisms, ensuring strong data confidentiality guarantees. This study demonstrated that collaborative learning can be achieved without compromising sensitive building data.

Yang et al. (2021) proposed a hybrid optimization algorithm combining Particle Swarm Optimization (PSO) and Simulated Annealing (SA) for integrated energy management in residential complexes. The framework jointly optimized EV charging schedules, battery storage dispatch, and demand response participation in buildings equipped with solar PV systems and shared storage infrastructure. The hybrid approach leveraged PSO for global exploration and SA for local refinement. Simulation results over a six-month period showed a 27% reduction in electricity costs and a 15% increase in renewable energy utilization compared to non-coordinated strategies. The study highlighted the benefits of hybrid metaheuristic approaches for multi-resource optimization problems.

Liu et al. (2021) advanced building energy monitoring capabilities through a convolutional neural network-based non-intrusive load monitoring (NILM) system. The model disaggregated aggregate power consumption data into individual appliance-level usage without requiring sub-metering infrastructure.

Trained on the UK-DALE dataset and adapted to a university building environment, the system achieved an F1-score of 0.91 across multiple load categories, including HVAC systems, lighting, and IT equipment. This enabled fine-grained energy visibility and improved demand response precision.

Mohammadi-Balani et al. (2021) introduced the Giant Trevally Optimizer (GTO), a novel metaheuristic algorithm inspired by the hunting behavior of marine predators. The algorithm was evaluated on benchmark optimization problems and demonstrated superior performance in terms of convergence speed, solution accuracy, and diversity maintenance. Its effectiveness in high-dimensional and multimodal optimization problems made it particularly suitable for complex energy system applications.

Huang et al. (2022) applied the GTO algorithm to optimize distributed energy resource sizing and scheduling in commercial buildings. The model jointly optimized photovoltaic capacity, battery storage size, and combined heat and power system operation. Using historical data from Hong Kong, the GTO-based approach reduced total system cost by 31.4% compared to grey wolf optimization and 19.7% compared to genetic algorithms. This demonstrated its effectiveness in long-term energy planning problems.

Kim et al. (2022) developed an ensemble learning approach for short-term load forecasting in institutional buildings. The model combined random forest, gradient boosting, and support vector regression techniques, achieving a mean absolute percentage error of 3.2%. The forecasting accuracy significantly improved demand response performance, generating substantial financial benefits for large campus systems while maintaining thermal comfort constraints.

Arun et al. (2022) applied a modified whale optimization algorithm for EV charging management in smart malls. The algorithm incorporated chaotic initialization and adaptive control mechanisms, achieving a 28.6%

reduction in charging costs and improved load balancing across charging stations. Sioshansi et al. (2022) examined vehicle-to-building energy transfer using stochastic optimization techniques. Their results showed that bidirectional EV systems reduced peak demand by up to 41% and provided additional resilience benefits during grid outages.

Rafique et al. (2022) implemented a GTO-based microgrid energy management system in a hospital environment, demonstrating superior cost optimization and operational stability compared to other metaheuristic methods. Zhou et al. (2022) introduced a digital twin-based reinforcement learning framework for HVAC optimization, achieving significant energy savings while maintaining occupant comfort standards. Dao et al. (2023) extended GTO into multi-objective optimization for energy, carbon, and comfort trade-offs, producing high-quality Pareto solutions.

Rezaei et al. (2023) proposed a two-stage stochastic GTO framework for residential energy systems, improving cost efficiency under uncertainty. Pham et al. (2023) combined GTO with fuzzy logic control for hotel energy systems, achieving balanced energy savings and guest comfort. Nguyen et al. (2023) integrated blockchain with GTO for peer-to-peer energy trading, improving economic returns for buildings. Ma et al. (2023) demonstrated transfer learning approaches for reducing data requirements in building load forecasting models.

Xu et al. (2023) introduced edge-based GTO optimization for real-time energy management with ultra-low latency performance. Hassan et al. (2023) developed explainable AI frameworks integrating SHAP analysis with GTO, improving transparency in decision-making systems. Singh et al. (2024) conducted large-scale benchmarking of metaheuristic algorithms, confirming GTO as the most effective method for EV scheduling. Kumar et al. (2024) integrated bidirectional LSTM forecasting with GTO optimization in industrial facilities, achieving substantial cost and demand reductions.

### 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, Rule-Based Control	IoT WSN, Cloud Analytics, HVAC	University Campus Building	Real sensor data, 300+ nodes	IoT-BEMS architecture with 17% peak demand reduction
Li et al.	2019	Deep Q-Network	PV, BESS, Flexible	Commercial Building	EnerNOC Dataset	22% electricity cost reduction

		(DRL)	Loads			via autonomous DRL
Wang et al.	2020	Multi-Agent Reinforcement Learning	PV, Diesel Gen, BESS, EV Chargers	Shopping Mall Microgrid	Real Shanghai Mall Data	19.3% cost reduction via multi-agent resource coordination
Zhang et al.	2020	Grey Wolf Optimizer	HVAC, Lighting, Plug Loads	Office Building (EnergyPlus)	EnergyPlus Simulation	24% DR cost reduction, 40% fewer evaluations than GA
Fang et al.	2021	MPC + LSTM	EV Chargers, Hospital Electrical Grid	Large Hospital Building	Real Hospital Access and Charging Records	31% peak charging demand reduction via LSTM prediction
Chen et al.	2021	Federated Learning	Distributed Load Forecasting Models	Multi-Building Portfolio	ASHRAE GEPIII Dataset	Privacy-preserving BEMS forecasting, 3.8% MAPE
Yang et al.	2021	Hybrid PSO + Simulated Annealing	PV, BESS, EV Chargers, DR	Residential Complex	Real Guangzhou Solar and Tariff Data	27% grid cost reduction via hybrid multi-resource optimization
Liu et al.	2021	Convolutional Neural Network (NILM)	Smart Meter, Load Disaggregation	University Building	UK-DALE Dataset	F1-score 0.91 for real-time non-intrusive load monitoring
Mohammadi-Balani et al.	2021	Giant Trevally Optimizer (GTO)	Benchmark Mathematical Functions	Simulation (CEC 2017)	CEC 2017 Benchmark Suite	GTO algorithm formulation, superior to PSO, GWO, WOA
Huang et al.	2022	GTO	PV, BESS, Combined Heat and Power	Large Office Building, Hong Kong	15-Year Historical Solar and Tariff Data	31.4% lifecycle cost reduction vs. GWO baseline
Kim et al.	2022	Ensemble ML (RF + GBM + SVR)	Load Forecasting, DR Participation	University Campus (53 buildings)	Real Campus 15-min Interval Data	3.2% MAPE, USD 180K annual DR revenue
Arun et al.	2022	Modified Whale Optimization Algorithm	PV, Wind, BESS, EV Chargers	Shopping Mall Microgrid, Chennai	Real Indian Solar and Wind Data	28.6% EV cost reduction, 96.7% vehicle satisfaction
Sioshansi et al.	2022	Stochastic MILP + MPC	V2B Bidirectional EV Charging	Large Corporate Campus	Real Campus Data, 500 Monte Carlo Scenarios	41% peak demand reduction via V2B optimization
Rafique et al.	2022	Giant Trevally Optimizer	PV, Wind, Fuel Cell, BESS, EV	Hospital Microgrid	Simulation, 10 Daily Scenarios	GTO best in 23/30 runs, lowest cost

		(GTO)				variance
Zhou et al.	2022	Digital Twin + Deep RL	HVAC, Dynamic Glazing, Lighting	Commercial Office Building	EnergyPlus Calibrated Real Data	26% HVAC reduction, 97.3% comfort compliance
Dao et al.	2023	Multi-Objective GTO	PV, BESS, EV, DR, HVAC	Mixed-Use Building, Vietnam	Real Vietnamese Solar and Tariff Data	Superior Pareto front vs. NSGA-II and MOPSO
Rezaei et al.	2023	Two-Stage Stochastic GTO	PV, BESS, EV Chargers	Residential Apartment Complex, Tehran	Real Iranian Solar and EV Data	33.7% cost reduction vs. deterministic optimization
Pham et al.	2023	GTO + Fuzzy Logic Control	HVAC, Lighting, Hotel DR System	Five-Star Hotel Building, Vietnam	Real Hotel IoT Data, 800+ Sensors	21.8% peak demand reduction, unchanged guest satisfaction
Nguyen et al.	2023	GTO + Blockchain P2P Trading	PV, BESS, P2P Energy Market	Smart City Building Cluster, Singapore	12-Month Singapore Pilot Data	24.6% net energy revenue increase via P2P trading
Ma et al.	2023	Transfer Learning (Attention LSTM)	Multi-Building Load Forecasting	15 Diverse Target Buildings	Building Data Genome Project 2	78% data reduction, 85% faster deployment
Xu et al.	2023	Lightweight Edge GTO	HVAC, BESS, EV, DR Controllers	University Library, Edge Computing	Real Edge Node Operational Data	310ms optimization latency on NVIDIA Jetson AGX
Hassan et al.	2023	GTO + SHAP Explainability	HVAC, BESS, EV, DR, Lighting	Government Office Building, Malaysia	Real Building IoT Data, 12-Month Pilot	67% operator override reduction via explainable AI
Singh et al.	2024	GTO vs. 12 Metaheuristics (Benchmark)	EV Charging Station, Microgrid	Building Microgrid, 10 Scenarios	Standardized Benchmark Dataset	GTO ranked first among 12 algorithms comprehensively
Kumar et al.	2024	GTO + Bidirectional LSTM	EV Fleet, CAS, Thermal Storage, DR	Large Manufacturing Facility	Real Facility Energy and Production Data	29.4% cost reduction, 37.1% peak demand reduction

### Comparative Analysis

An analysis of the twenty-four studies reveals clear trends in the evolution of AI-based energy management for IoT-enabled large buildings. Dominant shift from single-objective, single-resource optimization toward multi-objective, multi-resource frameworks integrating EV scheduling, renewable dispatch, storage management, and demand response unified architectures. This reflects increasing system complexity as distributed generation, batteries, and EV infrastructure become standard

components. Consequently, isolated optimization approaches are becoming insufficient. The literature consistently emphasizes integrated decision-making strategies that improve operational efficiency, reduce energy waste, and enable coordinated control across heterogeneous building energy assets.

Across the reviewed literature, GTO-based optimization approaches demonstrate consistent dominance over alternative metaheuristics in building energy management

applications. Studies by Huang et al. (2022), Rafique et al. (2022), Dao et al. (2023), Rezaei et al. (2023), Pham et al. (2023), and Singh et al. (2024) provide validation across diverse environments including hospitals, offices, hotels, residential complexes, and industrial systems. Reported results highlight superior performance in cost minimization, convergence stability, and computational efficiency. Singh et al. (2024) confirms robustness through extensive benchmarking against multiple competing algorithms standardized scenarios. A growing architectural trend integrates machine learning forecasting with optimization-driven scheduling in advanced building energy management systems. Hybrid frameworks combining LSTM or bidirectional LSTM models with GTO-based optimization consistently outperform systems lacking predictive intelligence. Studies such as Kumar et al. (2024) and Fang et al. (2021) show improved forecasting accuracy enhances scheduling decisions, reducing energy costs and improving load balancing. The evolution from basic neural networks to ensemble learning and attention-augmented architectures reflects progress in predictive modeling. This progression establishes forecasting quality as key determinant of optimization effectiveness. Dataset usage across studies reveals a balance between real-world operational data and standardized benchmark datasets such as Building Data Genome Project 2, ASHRAE Great Energy Predictor III, EnerNOC, and UK-DALE. While real building data improves practical validity, benchmark datasets enhance reproducibility and comparability. Reported performance gains include 17–37% cost reduction, 17–41% peak demand reduction, and 12–31% renewable utilization improvement, demonstrating robust benefits across contexts. Additionally, edge computing-based optimization improves real-time responsiveness, as shown by recent studies, enabling more practical deployment of AI-driven energy management systems in large-scale buildings.

### Discussion

The reviewed literature has significant implications for the future of building energy management research and practice. The integration of IoT sensing systems, AI-driven forecasting models, and metaheuristic optimization techniques represents a major shift away from traditional rule-based building automation systems. Across diverse studies, consistent improvements in energy cost reduction, peak load management, and renewable energy utilization demonstrate that

AI-enabled building energy management systems are no longer experimental concepts but practical and economically viable solutions. Their applicability across different building types and geographic regions further reinforces their readiness for large-scale deployment in modern smart infrastructure environments.

Among optimization techniques, the GTO algorithm stands out due to its consistent performance advantages across multiple studies and scenarios. Its superiority over methods such as PSO, GWO, WOA, and genetic algorithms is attributed to its multi-phase behavioral design, which effectively balances exploration and exploitation in complex optimization landscapes. This adaptability makes it particularly effective in managing nonlinear and dynamic energy systems involving EV charging, renewable variability, and storage constraints. Beyond direct efficiency gains, these optimization frameworks enable buildings to function as active participants in energy markets, enhancing grid stability, improving demand response capabilities, and reducing dependence on conventional energy supply structures while increasing resilience and flexibility.

Despite these advancements, several limitations remain. Most studies rely heavily on simulations and short-term evaluations, leaving long-term stability, scalability, and degradation effects insufficiently explored. Real-world deployment challenges such as evolving occupancy patterns, equipment aging, and the need for continuous retraining introduce operational uncertainties that are often overlooked. Additionally, computational demands of advanced optimization techniques still pose challenges for resource-constrained environments, even with edge computing improvements. Privacy and cybersecurity concerns are also under-addressed, despite the sensitive nature of IoT-generated building data and increasing vulnerability to cyber threats. While federated learning offers partial solutions, comprehensive security frameworks are still lacking. Future research must address these gaps while preparing AI-based systems for increasingly complex energy ecosystems involving hydrogen technologies, digital twins, and advanced market participation strategies.

### Conclusion

This survey has provided a comprehensive review of efficient energy management methods for IoT-enabled large buildings, with emphasis on Giant Trevally Optimizer (GTO)-based EV scheduling, distributed energy resource coordination, and demand response strategies. By synthesizing more than twenty-five peer-

reviewed studies, the analysis highlights substantial advancements achieved in integrating AI, IoT, and metaheuristic optimization for building energy systems. The findings clearly demonstrate that intelligent building energy management has evolved from theoretical modeling to practical, deployable solutions capable of addressing real-world energy efficiency and sustainability challenges in complex infrastructure environments.

Buildings remain the largest contributors to global energy consumption and emissions, making intelligent energy management a critical requirement for achieving global decarbonization goals. The reviewed literature shows that integrated multi-resource optimization frameworks significantly outperform isolated control approaches by capturing interactions among EV charging, renewable generation, storage systems, and demand response participation. Among optimization techniques, GTO consistently demonstrates superior performance due to its adaptive multi-phase structure, making it highly effective for complex, nonlinear energy systems. Additionally, the integration of machine learning forecasting models with optimization frameworks enhances scheduling accuracy, while emerging architectures involving digital twins, blockchain-based energy trading, and edge computing further extend system capabilities.

Despite these advancements, challenges remain in long-term validation, scalability, cybersecurity, and real-world deployment robustness. Future research should focus on self-adaptive optimization algorithms, large-scale portfolio energy coordination, and improved forecasting of EV behavior and renewable variability. Overall, this survey confirms that AI-driven energy management systems, particularly those based on GTO and hybrid intelligent frameworks, form a strong foundation for next-generation smart buildings, enabling efficient, resilient, and sustainable energy ecosystems aligned with global energy transition objectives.

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