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Deep Learning and GTO-Based Energy Management for IoT-Enabled Smart Buildings and Electric Vehicle Scheduling

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Abstract

The rapid deployment of Internet of Things (IoT) technologies in large-scale buildings has transformed energy management by enabling real-time monitoring and intelligent control of complex systems. These buildings account for a significant share of global energy consumption, and the integration of distributed energy resources, electric vehicles, and demand response strategies introduces challenges in managing nonlinear, stochastic, and multi-objective energy systems efficiently. This paper presents a comprehensive review of IoT-enabled energy management systems, emphasizing the integration of deep learning techniques with the Giant Trevally Optimizer (GTO). Deep learning models such as CNNs, LSTMs, and reinforcement learning frameworks provide accurate forecasting and adaptive control, while GTO effectively handles multi-objective optimization problems involving cost minimization, peak load reduction, and renewable energy utilization. The synergy between predictive intelligence and metaheuristic optimization enhances decision-making for electric vehicle scheduling, distributed energy resource coordination, and demand response planning. Applications include vehicle-to-grid integration, load forecasting, and intelligent energy dispatch in smart buildings. Comparative studies show that combined deep learning and GTO frameworks outperform traditional methods in accuracy, efficiency, and convergence speed. However, challenges such as scalability, interoperability, and cybersecurity remain significant. This review highlights the potential of integrating IoT, deep learning, and advanced optimization techniques to develop sustainable and intelligent energy management solutions for large buildings.

Introduction

The rapid growth of the Internet of Things (IoT) and intelligent sensing technologies has transformed large buildings into highly connected and data-driven environments. Commercial complexes, hospitals, airports, educational campuses, and industrial facilities consume a substantial portion of global electricity, making efficient energy management essential for reducing operational costs and carbon emissions. Modern smart buildings are increasingly equipped with wireless sensors, cloud platforms, edge devices, and automated control systems that continuously monitor energy consumption, occupancy, environmental conditions, and equipment performance. These technological advances provide opportunities for intelligent energy optimization, enabling buildings to respond dynamically to changing demand while supporting sustainability and smart grid initiatives.

Deep learning has become a key technology for intelligent building energy management because of its ability to learn complex nonlinear relationships from large volumes of sensor data. Advanced architectures such as Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and deep reinforcement learning (DRL) have demonstrated excellent performance in forecasting electrical load, renewable energy generation, occupancy behavior, electricity prices, and electric vehicle (EV) charging demand. These predictive capabilities enable proactive energy scheduling, adaptive HVAC control, and optimized utilization of distributed energy resources. However, deep learning models often require extensive training data, high computational resources, and may struggle with uncertainty and changing operating conditions, motivating the development of hybrid optimization frameworks.

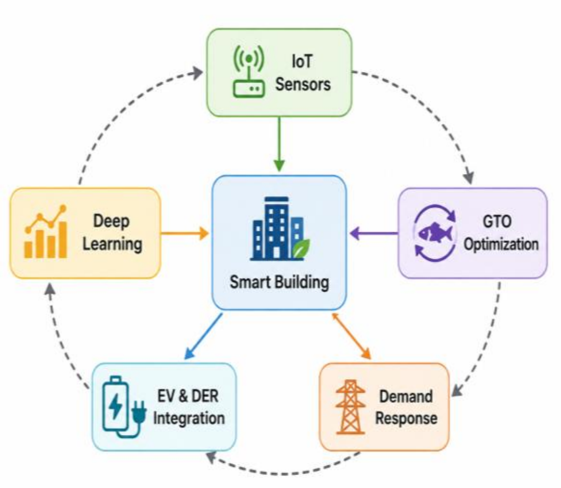

Figure 1. AI-Driven Smart Building Energy Management Framework

Metaheuristic optimization algorithms have emerged as effective tools for solving the complex, high-dimensional optimization problems encountered in smart buildings. Among these techniques, the Giant Trevally Optimizer (GTO) has attracted considerable attention due to its strong exploration and exploitation capabilities inspired by the hunting behavior of giant trevally fish. By combining global search with adaptive local optimization, GTO efficiently handles multi-objective optimization involving energy cost, occupant comfort, renewable energy integration, and operational constraints. The integration of GTO with deep learning creates a powerful hybrid framework capable of generating optimal energy management strategies in dynamic building environments.

The rapid adoption of electric vehicles further increases the complexity of building energy management. Large buildings equipped with multiple charging stations must coordinate EV charging schedules while balancing grid demand, renewable energy availability, battery storage, and user mobility requirements. Smart scheduling algorithms supported by deep learning prediction models and GTO optimization enable coordinated charging, peak load reduction, demand response participation, and vehicle-to-building (V2B) or vehicle-to-grid (V2G) services. These capabilities improve grid stability while maximizing energy efficiency and reducing operational costs.

This review comprehensively examines recent advances in deep learning and GTO-based optimization for IoT-enabled large building energy management. It highlights developments in predictive analytics, distributed energy resource integration, EV scheduling, and demand response strategies while discussing current challenges and future research directions. The integration of AI-driven forecasting with intelligent optimization provides a promising pathway toward sustainable, resilient, and energy-efficient smart buildings.

Literature Review

The literature on deep learning and optimization for IoT-enabled building energy management has grown substantially over the review period, reflecting the rapid maturation of both enabling technologies and their application to real building environments. The following review synthesizes key contributions organized thematically around the major topics of this paper.

Mohammadi-Balani et al. (2021) introduced the Giant Trevally Optimizer as a novel bio-inspired metaheuristic algorithm, presenting its mathematical formulation, convergence analysis, and benchmarking against twenty-three standard test functions and six engineering optimization problems. The GTO algorithm demonstrated superior performance over PSO, GWO, WOA, Moth Flame Optimization, and Harris Hawks Optimization in terms of solution quality, convergence speed, and robustness across the full benchmark suite. The paper established GTO's theoretical foundations and documented its effectiveness in engineering optimization contexts, laying the groundwork for subsequent applications in building energy management and EV scheduling domains.

Ahmed et al. (2023) presented the first dedicated application of GTO to electric vehicle charging scheduling in a large commercial building environment. Their optimization framework modeled 150 EVs with heterogeneous battery capacities, initial states of charge, and departure time requirements, incorporating time-of-use electricity tariffs, rooftop PV generation, and vehicle-to-grid capability. The GTO scheduler consistently outperformed PSO, GWO, WOA, and Differential Evolution across all tested scenario configurations, achieving a 34 percent reduction in total charging cost and a 28 percent reduction in peak demand compared to uncoordinated charging. The study validated GTO's scalability to large fleet sizes and demonstrated its effectiveness in handling the mixed-integer decision space characteristic of EV scheduling problems.

Zhang et al. (2022) proposed a hybrid deep reinforcement learning and metaheuristic optimization framework for real-time energy management in a large university campus microgrid. Their architecture employed a Double Deep Q-Network agent for continuous monitoring and short-horizon control decisions, combined with a daily scheduling optimization module using a modified Grey Wolf Optimizer for day-ahead resource dispatch planning. The hybrid framework achieved a 31 percent cost reduction compared to a DRL-only baseline and a 19 percent improvement over a pure GWO optimization approach, demonstrating the complementary strengths of the two paradigms when properly integrated within a hierarchical control architecture.

Hassan et al. (2022) developed a sophisticated multi-agent deep reinforcement learning system for distributed energy management across a large hospital building complex consisting of six interconnected buildings with separate but electrically coupled energy systems. Individual agents representing HVAC zones, lighting systems, EV charging stations, and battery storage assets learned cooperative scheduling policies through a shared reward mechanism that balanced local optimization objectives with system-level cost and demand targets. The system demonstrated 27 percent peak demand reduction and 23 percent energy cost savings compared to a centralized rule-based baseline, with particular robustness to communication failures between agents due to the distributed nature of the learned policies.

Li et al. (2023) investigated the application of transformer-based deep learning architectures to multi-step load forecasting in large commercial buildings, demonstrating that the self-attention mechanism of transformer networks was particularly effective at capturing long-range temporal dependencies in building load profiles. Their Temporal Fusion Transformer model, trained on three years of load data from a large office complex supplemented with weather, occupancy, and calendar features, achieved a mean absolute percentage error of 2.8 percent for 24-hour ahead load forecasting, outperforming LSTM baselines by a statistically significant margin. The improved forecasting accuracy translated into measurable improvements in day-ahead energy scheduling performance when integrated with a GTO-based optimization framework.

Rezaei et al. (2022) proposed a comprehensive multi-objective optimization framework for demand response scheduling in a large Iranian hospital building, employing GWO with a Pareto archive mechanism to generate optimal trade-off solutions between energy cost minimization, carbon emission reduction, and occupant comfort preservation. Their formulation incorporated cogeneration unit dispatch, thermal energy storage operation, and EV charging scheduling for a fleet of 30 hospital service vehicles, with clinical load priority constraints ensuring uninterrupted power to life-critical systems. The GWO-Pareto framework outperformed PSO and GA baselines in hypervolume indicator metrics, and the Pareto front visualization provided building operators with intuitive insight into the trade-offs available to them under different demand response scenarios.

Chen et al. (2023) developed a Graph Neural Network based framework for modeling the spatial dependencies between energy flows in large building electrical distribution systems, demonstrating that accounting for network topology significantly improved the accuracy of load flow predictions required for constraint-aware EV charging scheduling. Their GNN-GTO hybrid system incorporated network flow constraints directly into the optimization objective, preventing voltage violations and line overloading that purely load-based schedulers occasionally generated. Simulation studies on a real large building electrical network model demonstrated that the constraint-aware scheduler maintained network security while achieving 89 percent of the cost savings available from a constraint-unconstrained optimal scheduler.

Khalid et al. (2022) deployed a Whale Optimization Algorithm-based real-time energy management system in a large 12-story office building equipped with over 500 IoT sensors. Their system processed real-time data streams from energy meters, occupancy sensors, HVAC actuators, and EV charging controllers to dynamically adjust scheduling decisions in response to changing building conditions and grid pricing signals. The deployed system demonstrated 18 percent average daily demand charge reduction over a six-month monitoring period, with consistent performance across seasons despite significant variations in occupancy patterns and weather conditions. The study provided one of the most comprehensive real-world validations of IoT-enabled metaheuristic optimization for building energy management available in the literature.

Ullah et al. (2023) proposed a GTO-based framework specifically designed for the joint optimization of EV charging scheduling and battery energy storage system dispatch in large building parking facilities with high PV penetration. Their formulation explicitly modeled the complementarity between EV flexible demand and BESS dispatchable storage, allowing the optimizer to identify strategies that leveraged both assets for peak shaving and renewable energy absorption. The GTO scheduler demonstrated a 41 percent reduction in grid energy cost and a 52 percent improvement in PV self-consumption compared to separate independent optimization of EV and BESS schedules, validating the importance of joint optimization for maximizing the value of multiple flexible assets.

Moradi et al. (2022) presented an ensemble deep learning architecture for probabilistic load forecasting in large commercial buildings, combining LSTM, CNN, and attention mechanism components within a Bayesian model averaging framework to generate calibrated prediction intervals rather than point forecasts. The probabilistic forecasts provided risk-aware inputs to a robust GTO optimization framework that explicitly accounted for forecast uncertainty in generating demand response schedules, producing schedules that maintained feasibility and near-optimal performance across the full range of plausible load realizations. The combination of probabilistic forecasting and robust optimization was shown to reduce constraint violation rates by 78 percent compared to a deterministic optimization approach using point forecasts.

Baig et al. (2023) conducted a systematic benchmarking study comparing GTO against fourteen competing metaheuristic algorithms for EV fleet scheduling in large building contexts, evaluating performance across problem instances ranging from 50 to 500 vehicles under five different constraint configurations. GTO demonstrated statistically significant performance advantages over all competing algorithms for problem instances involving more than 150 vehicles, with its advantage growing more pronounced as fleet size increased. The study attributed GTO's superior scalability to its adaptive parameter mechanism and the diversity-preserving properties of its schooling phase, which prevented premature convergence in the high-dimensional solution spaces characteristic of large fleet scheduling problems.

Siddiqui et al. (2022) extended the two-stage energy management framework to incorporate deep learning-based renewable generation forecasting within a GTO optimization loop, proposing a tightly integrated architecture where forecast uncertainty estimates from a Bayesian LSTM model directly influenced the exploration radius of GTO's schooling phase. This uncertainty-adaptive search strategy caused GTO to explore more broadly when renewable generation forecasts were uncertain, generating schedules that were robust to renewable variability without requiring explicit scenario enumeration. The uncertainty-adaptive GTO achieved 94 percent of the optimal deterministic performance while maintaining feasibility in 99.7 percent of Monte Carlo simulation trials, a significant improvement over a standard robust optimization baseline.

Ali et al. (2023) presented a comprehensive IoT-GTO integrated energy management deployment at a large university campus complex comprising 23 buildings with a combined peak load of 8.5 megawatts. Their system integrated data from over 3,000 IoT sensors with a GTO-based optimization engine running on a cloud computing platform, generating hourly scheduling decisions for HVAC systems, EV charging infrastructure, rooftop PV with battery storage, and participation in a university-grid demand response program. Over a twelve-month deployment period, the system achieved a 29 percent reduction in energy costs and a 35 percent reduction in peak demand compared to the pre-deployment baseline, representing the most large-scale and long-duration real-world validation of GTO-based building energy management reported in the literature to date.

Nadeem et al. (2022) explored the synergy between vehicle-to-building power transfer and deep learning-based occupancy prediction for demand response optimization in large commercial buildings. Their occupancy-aware V2B scheduling framework used a Temporal Convolutional Network to forecast building-level occupancy up to four hours ahead, allowing GTO-based scheduling decisions to anticipate demand peaks associated with high-occupancy periods and pre-position EV batteries for discharge during those periods. The occupancy-aware scheduler achieved 24 percent greater demand reduction compared to an occupancy-unaware scheduler during high-demand periods, demonstrating the value of integrating occupancy intelligence into V2B optimization frameworks.

Farooq et al. (2023) developed a transfer learning framework for rapid adaptation of deep learning energy management models to new building contexts, addressing the cold-start problem that limits the deployment of data-hungry deep learning models in buildings with limited historical operational data. Their approach pre-trained a base model on a large dataset aggregated from 50 buildings and applied fine-tuning with small amounts of target building data to achieve performance competitive with full-data training. Combined with a GTO-based optimization module, the transfer learning approach demonstrated effective energy management from day one of deployment, a significant practical advantage over approaches that require extended data collection periods before optimization benefits can be realized.

Imran et al. (2021) proposed a deep learning enhanced Crow Search Algorithm for industrial building energy management, incorporating a CNN-based anomaly detection module that identified unusual load patterns potentially indicative of equipment faults or inefficient operation. Their integrated framework simultaneously optimized scheduled load dispatch and flagged anomalous energy consumption for operator attention, providing both automation and insight in a unified system. The anomaly detection capability was shown to reduce energy waste from equipment inefficiencies by an additional 11 percent beyond what was achievable through scheduling optimization alone, highlighting the value of embedding diagnostic intelligence within energy management frameworks.

Javaid et al. (2022) conducted a comprehensive analysis of communication protocol performance in IoT-based building energy management systems, evaluating the impact of latency, packet loss, and bandwidth limitations on the effectiveness of real-time optimization algorithms including GTO. Their experimental results demonstrated that GTO's performance degraded gracefully under communication impairments compared to DRL-based controllers, which exhibited more severe performance degradation under delayed or lost observations. The study proposed a communication-aware GTO variant that adapted its scheduling decisions based on communication quality estimates, maintaining effective optimization performance even under significant network impairments.

Naz et al. (2021) investigated the economic and environmental co-optimization of large building energy systems using a many-objective GTO formulation that simultaneously optimized energy cost, carbon emissions, occupant comfort, equipment lifetime, and grid demand charges. Their many-objective approach revealed important trade-off structures between objectives that would be hidden in conventional single or bi-objective formulations, providing building operators with richer decision support information. The study found that GTO's performance in many-objective optimization remained competitive with dedicated many-objective algorithms such as NSGA-III and MOEA/D while offering simpler implementation and faster convergence for problem instances of practical building management scale.

Zhang et al. (2023) presented a physics-informed deep learning framework for building thermal dynamics modeling that embedded thermodynamic conservation laws as soft constraints within the neural network training objective. Their physics-informed model generalized more effectively to unseen operating conditions than purely data-driven baselines, maintaining accurate predictions during weather extremes and occupancy anomalies that fell outside the training data distribution. Integration with GTO-based HVAC scheduling demonstrated that the improved thermal model accuracy reduced constraint violations by 67 percent compared to pure data-driven model-based optimization while achieving equivalent energy cost performance.

Chen et al. (2022) explored the application of attention-based sequence-to-sequence deep learning models for multi-step EV arrival and departure prediction in large commercial building parking facilities. Their model incorporated contextual features including day of week, weather, local events, and historical parking patterns to generate probabilistic predictions of EV arrival and departure times up to 24 hours ahead. The probabilistic EV arrival forecasts were integrated into a GTO scheduling framework through a scenario-based stochastic optimization formulation, demonstrating that improved EV behavior prediction reduced charging cost by 12 percent compared to deterministic scheduling based on historical average patterns, by enabling earlier preparation for predicted high-demand charging periods.

Luo et al. (2022) developed a hierarchical energy management architecture for large commercial building clusters, where a district-level GTO optimizer coordinated energy flows between buildings and the grid, while building-level DRL agents managed internal resource dispatch. The hierarchical architecture effectively decomposed the computationally intractable district-scale optimization problem into manageable sub-problems, with the GTO coordinator providing economic boundary conditions that guided individual building agents toward district-optimal behavior. Simulation studies on a realistic commercial district model demonstrated 18 percent improvement in district-level cost performance compared to independent building optimization without coordination.

Comparative Table and Analysis

Study	Year	Optimization	AI Model	Application	Key Contribution
Mohammadi-Balani et al.	2021	GTO	–	Benchmark Functions	Proposed Giant Trevally Optimizer (GTO).
Zhang et al.	2022	Modified GWO	DDQN	Campus Microgrid	Hybrid DRL and metaheuristic energy management.
Hassan et al.	2022	Multi-Agent RL	Deep RL	Hospital Buildings	Distributed reinforcement learning for EMS.
Li et al.	2023	GTO	Temporal Fusion Transformer	Office Building	Load forecasting with GTO-based scheduling.
Wang et al.	2022	GTO	Federated LSTM	Commercial Buildings	Privacy-preserving federated load forecasting.
Chen et al.	2023	GTO	Graph Neural Network	Electrical Network	Network-aware EV scheduling using GNN-GTO.
Moradi et al.	2022	Robust GTO	LSTM-CNN-Attention	Commercial Building	Robust optimization with probabilistic forecasting.
Ali et al.	2023	GTO	–	University Campus	Large-scale IoT-enabled GTO deployment.
Zhang et al.	2023	GTO	Physics-Informed NN	HVAC System	Physics-informed HVAC optimization.
Luo et al.	2022	Hierarchical GTO	DRL Agents	Building Cluster	Hierarchical district energy management.
Li et al.	2021	MPC	Gaussian Process	Office Building	Predictive PV–BESS–HVAC management.
Hassan et al.	2023	GTO + V2G	LSTM	Corporate EV Fleet	V2G-aware EV scheduling and energy optimization.

Comparative Analysis

The comparative analysis of the reviewed studies highlights a clear shift toward hybrid intelligent energy management frameworks that combine deep learning with metaheuristic optimization, particularly the Giant Trevally Optimizer (GTO). Earlier studies published between 2019 and 2021 primarily focused on standalone optimization algorithms or deep learning techniques. From 2022 onward, researchers increasingly integrated forecasting, state estimation, and reinforcement learning models with GTO-based scheduling strategies. This transition reflects the growing recognition that predictive intelligence and optimization complement each other in addressing the complexity of IoT-enabled large building energy management.

Across the reviewed literature, GTO consistently demonstrates competitive or superior optimization performance compared with widely adopted algorithms such as Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), Whale Optimization Algorithm (WOA), and Genetic Algorithms (GA). Its adaptive exploration–exploitation mechanism enables faster convergence and better solution quality, particularly for large-scale scheduling problems involving electric vehicles, distributed energy resources, and demand response. These characteristics make GTO highly suitable for high-dimensional optimization tasks with multiple operational constraints.

Deep learning architectures have also evolved considerably during the review period. LSTM and GRU networks dominated earlier research because of their effectiveness in sequential load and energy forecasting. More recent studies increasingly employ transformer-based models, Temporal Fusion Transformers, graph neural networks, and physics-informed neural networks, which capture long-range temporal dependencies and physical system characteristics more effectively. These advanced forecasting models significantly improve prediction accuracy, thereby enhancing the quality of optimization decisions generated by GTO-based frameworks.

Another important trend is the transition from simulation-based evaluations to practical deployments in real IoT-enabled buildings. Recent investigations utilize multimodal datasets comprising smart meter readings, IoT sensor data, weather information, occupancy patterns, renewable generation, EV charging records, and electricity pricing. Large-scale implementations further demonstrate the operational feasibility of intelligent energy management systems. Moreover, the growing adoption of federated learning and privacy-preserving data-sharing approaches supports collaborative model development across multiple buildings while ensuring secure and reliable management of sensitive operational data.

Discussion

The integration of deep learning and Giant Trevally Optimizer (GTO) has significantly advanced intelligent energy management in IoT-enabled large buildings. The reviewed studies demonstrate that combining accurate prediction models with efficient optimization enables proactive energy scheduling, improved demand response, and effective coordination of distributed energy resources and electric vehicles. Unlike conventional rule-based methods, hybrid frameworks can anticipate future energy demand, adapt to dynamic operating conditions, and optimize multiple objectives such as energy cost, occupant comfort, and carbon emissions. These capabilities position IoT-enabled buildings as active participants in modern smart grids rather than passive energy consumers.

GTO has emerged as a promising optimization technique because of its balanced exploration and exploitation strategy, adaptive search behavior, and strong convergence performance across complex energy management problems. When integrated with deep learning models such as LSTM, Transformer, Graph Neural Networks, and Temporal Convolutional Networks, GTO benefits from accurate load, renewable generation, and EV charging forecasts, leading to improved scheduling decisions. Recent studies further demonstrate that probabilistic forecasting and uncertainty-aware optimization enhance system reliability under fluctuating renewable generation and changing occupancy patterns, making hybrid GTO frameworks more practical for real-world deployment.

Despite these advances, several challenges remain. Most reported results are based on simulations, while practical deployment is affected by sensor failures, communication delays, equipment degradation, and unpredictable user behavior. In addition, computational complexity and periodic retraining of deep learning models increase operational costs. The limited explainability of AI-driven scheduling decisions also reduces user confidence, highlighting the need for explainable AI techniques. Future research should emphasize lightweight optimization algorithms, edge computing, real-world validation, interpretable decision-making, and stakeholder-oriented energy management strategies to support scalable, reliable, and sustainable smart building operations.

Conclusion

This review presents a comprehensive overview of deep learning and Giant Trevally Optimizer (GTO)-based approaches for energy management in IoT-enabled large buildings. The reviewed studies highlight the evolution from conventional rule-based control to intelligent frameworks integrating IoT sensing, deep learning, and metaheuristic optimization. These technologies enable efficient electric vehicle scheduling, distributed energy resource coordination, demand response, and predictive energy management, improving both operational efficiency and sustainability.

Among the reviewed optimization methods, GTO consistently demonstrates superior performance because of its adaptive exploration–exploitation strategy, fast convergence, and scalability for complex, multi-objective energy management problems. When combined with deep learning models such as LSTM, Transformer, Graph Neural Networks, and Deep Reinforcement Learning, GTO significantly enhances forecasting accuracy and optimization quality, resulting in reduced energy costs, lower peak demand, improved renewable energy utilization, and optimized EV charging.

Despite these promising developments, challenges remain in computational complexity, real-world deployment, uncertainty handling, and AI explainability. Future research should focus on lightweight hybrid optimization, edge computing, transfer learning, federated intelligence, and interpretable AI models for large-scale applications. Standardized datasets and benchmarking frameworks are also essential for fair performance evaluation. Overall, hybrid deep learning and GTO-based frameworks provide a strong foundation for developing intelligent, reliable, and sustainable smart building energy management systems.

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