Architectures, Algorithmic Optimization, and Security Frameworks for Smart Home Energy Management Systems: A Comprehensive Synthesis

Abstract

Smart home energy management systems have emerged as a critical technological bridge between residential demand-side flexibility and grid modernization. Modern architectures coordinate heterogeneous end-use loads, distributed energy resources, and dynamic retail electricity tariffs across multi-tiered edge, fog, and cloud computing environments. This synthesis examines the architectural paradigms, predictive forecasting models, algorithmic optimization frameworks, behind-the-meter asset integration strategies, and cybersecurity mechanisms documented in recent smart home energy management literature. Reported findings indicate that hybrid metaheuristic scheduling, mathematical programming, and reinforcement learning techniques yield substantial reductions in household electricity expenses and peak demand across diverse pricing environments. However, performance outcomes remain highly sensitive to regional tariff structures, battery degradation dynamics, occupant comfort boundaries, and computational constraints. Simultaneously, the expanding connectivity of internet-of-things devices introduces significant operational vulnerabilities, necessitating lightweight cryptography, zero-trust perimeter verification, and decentralized privacy-preserving governance. By synthesizing empirical evaluations, hardware prototypes, and simulation studies, this report clarifies the operational trade-offs governing automated residential energy management and outlines the empirical validation required to resolve current deployment barriers.

Contents

1 Introduction

The rapid expansion of distributed renewable generation, residential battery storage, and electrified transport has intensified the need for intelligent demand-side management at the residential edge. Smart home energy management systems address this challenge by orchestrating appliance schedules, energy storage systems, and local photovoltaic generation in response to time-varying retail price signals and grid constraints [1, 2]. Contemporary deployments increasingly transition from purely centralized cloud platforms to tiered edge-fog-cloud architectures that partition computational workloads to overcome transmission latency, mitigate bandwidth constraints, and support real-time appliance dispatch [1, 3]. Within these distributed systems, automated control frameworks aim to balance competing objectives, including the minimization of household electricity expenditures, the reduction of peak-to-average power ratios, the preservation of occupant thermal and operational comfort, and the extension of physical asset lifetimes [4–6].

This synthesis provides an evidence-driven analysis of smart home energy management systems, focusing on physical sensing and edge-fog computational architectures, load forecasting and digital twin integrations, algorithmic scheduling and reinforcement learning methods, behind-the-meter asset coordination, and cybersecurity frameworks. The evidence boundary encompasses peer-reviewed empirical field trials, embedded hardware testbeds, and numerical simulation studies across diverse tariff and climate conditions. The review does not claim comprehensive coverage of macro-grid transmission dynamics or commercial-industrial demand response except where directly interfacing with residential aggregation and prosumer transactive frameworks.

2 Edge-to-Cloud IoT Sensing Infrastructures and Non-Intrusive Load Monitoring Architectures

Modern smart home energy management infrastructures operate across tiered edge, fog, and cloud computational layers to capture, transmit, and analyze residential power consumption [2]. While conventional residential demand-side management platforms rely heavily on centralized cloud processing, remote cloud analytics can introduce latency barriers that hinder real-time control and immediate demand-response actions [1]. To resolve this latency mismatch, contemporary architectures increasingly partition analytical workloads between on-site sensing hardware, intermediary fog nodes, and centralized cloud repositories [1, 2]. In these configurations, embedded hardware hubs, IoT middleware gateways, and cloud platforms coordinate both smart and legacy home appliances to automate load scheduling, deliver proactive user notifications, and facilitate demand response programs [3, 7, 8].

At the physical sensing and local communication layer, systems deploy specialized smart meters, embedded smart plugs, and low-power wireless networking to monitor granular electrical parameters [9–11]. Dedicated smart plugs record root-mean-square voltage, current, active power, reactive power, frequency, power factor, and admittance, routing these measurements via Zigbee or WI-SUN home area networks to local controllers and smart meters [10, 11]. Open middleware architectures also employ WI-SUN field area networks to link residential metering interfaces with utility-side aggregation systems across multi-vendor devices [11]. At the local hardware level, low-cost microcontrollers, such as Arduino Mega 2560 platforms fitted with Wi-Fi shields, execute priority-based switching routines to mitigate peak power demands and reduce peak-to-average ratios [9]. Furthermore, embedded fog computing devices, such as a Raspberry Pi 3 Model B Rev 1.2 operating at 600 MHz, have demonstrated the capacity to run tiny machine learning classifiers locally, where a decision tree classifier achieved 100 percent appliance classification accuracy with 1.59 microseconds of inference latency and a support vector machine achieved 97 percent accuracy with 23 milliseconds of inference latency [10].

Complementing granular appliance-level sensing, machine learning models analyze correlated sensor streams and forecast household load trajectories [12, 13]. Deep neural networks implemented within machine learning software frameworks process IoT sensor feeds to anticipate consumption trends and provide real-time user feedback [12]. Because comprehensive multi-sensor deployments introduce financial and operational overhead, sensor reduction methods applying correlation analysis across diverse environmental inputs have been evaluated; in an HVAC energy forecasting setup utilizing six environmental sensor variables to predict power consumption, a gradient-boosting regressor yielded a root-mean-square error of 22.29, while the systematic elimination of low-importance redundant sensors reduced total hardware costs by 13 percent [13].

To circumvent the intrusive deployment of physical smart plugs across every individual load, non-intrusive appliance load monitoring architectures disaggregate composite power signals collected at central metering points [14, 15]. Within fog-cloud frameworks, such as those built upon the Tridium Niagara Framework, cognitive embedded IoT controllers serve as residential gateways running artificial neural network-based two-stage load disaggregation models to isolate specific appliance signatures without intrusive sub-metering [14]. Similarly, proof-of-concept testing using open middleware with active power data sampled at 5-second intervals (1/5 Hz) and a 60-to-40 percent training-to-test split confirmed that machine learning load disaggregation effectively tracks operational states of appliances like refrigerators, microwaves, and computer monitors [11]. These non-intrusive methods interface with local host platforms, allowing consumers to establish automated operating schedules aligned with regional tariff structures to curtail overall electricity expenditure [15].

Field deployments and empirical evaluations across residential and commercial settings demonstrate tangible energy and cost reductions alongside notable architectural limitations [3, 8, 10]. A multi-scenario residential deployment evaluating the Homergy platform over four weeks documented weekly energy savings of 0.5 kWh in a low-consumption home, 0.35 kWh in a single-user office, and a 13-kWh weekly improvement over smart-devices-only systems in a high-consumption household, where total first-month savings reached 25 kWh [3]. In a fog-computing prototype executing time-of-use demand response, daily electricity expenditure decreased by 30.26 percent, from approximately 9.22 USD to 6.43 USD per day [10]. In an industrial demand-side deployment across four corporate facilities, where weekly baseline gross consumption averaged approximately 1250 kWh and maximum demand peaked at 104 kW during HVAC startup, automated smart meter scheduling saved 17 kWh at 1:00 PM, 20 kWh at 3:00 PM, and 14 kWh at 6:00 PM during test evaluations compared to manual switching [8]. Nevertheless, existing implementations exhibit critical operational bounds: rule-based HVAC relays often switch loads on fixed timers without incorporating ambient indoor temperature, humidity, or occupancy dynamics [8], classifiers depend on comprehensive pre-training across residential appliance inventories, and smart metering interfaces remain vulnerable to potential dynamic pricing data manipulation [10].

3 Machine Learning-Driven Load Forecasting and Digital Twin Frameworks

Digital twin frameworks coupled with deep learning pipelines provide dynamic virtual representations of residential energy flows to address the volatility of renewable generation, flexible loads, and dynamic tariffs. Within simulated environments evaluated at 15-minute scheduling intervals, digital twin-assisted edge architectures incorporating Long Short-Term Memory networks for photovoltaic generation, electric vehicle availability, and appliance demand forecasting have demonstrated operational cost reductions of up to 10% through continuous model updates [16]. Complementary multi-stage architectures leverage one-dimensional deep convolutional neural networks for feature extraction from historical consumption traces, subsequently supplying these representations to Long Short-Term Memory networks to guide appliance scheduling algorithms aligned with occupant behavior [17].

Translating predictive pipelines into physical home environments depends on Internet of Things sensing hardware and model selection across multi-variable forecasting tasks. In experimental residential testbeds utilizing PZEM-004T sensors interfaced with ESP8266 controllers across two load zones, ensemble methods such as Random Forest achieved an average Root Mean Square Error of 0.060 09 for short-term load forecasting, demonstrating performance comparable to recurrent models such as Gated Recurrent Units (Root Mean Square Error of 0.062 75) and Bidirectional Long Short-Term Memory networks (Root Mean Square Error of 0.063 15) [18]. To capture pricing dynamics alongside load profiles, hybrid models optimized with Particle Swarm Optimization have been applied to multi-target time-series datasets; in an empirical evaluation using one year of household demand and pricing data, an optimized hybrid XGBoost model achieved relative performance gains of up to 36.6% in Root Mean Square Error, up to 36.8% in Mean Absolute Error, and up to 3.9 in R-squared over conventional machine learning baselines [19].

Deploying data-driven models directly within home energy management hardware requires balancing forecasting accuracy against computational overhead and data privacy constraints. Empirical evaluations across residential heat pump loads, base consumption, and solar photovoltaic generation under restricted CPU and memory configurations indicate distinct Pareto trade-offs: Stochastic Gradient Descent regressors maximized execution speed, Kolmogorov-Arnold Networks generally minimized Root Mean Square Error, and gradient-boosted decision trees captured peak demand fluctuations [20]. To preserve consumer data privacy without centralizing raw telemetry, federated learning frameworks train localized Long Short-Term Memory models on edge devices using calendar and weather features before global aggregation via Federated Averaging [21]. In simulations utilizing the UK Power Networks dataset, federated training matched the Root Mean Square Error accuracy of centralized baselines while reducing training time by up to one order of magnitude and cutting communication overhead up to 50 times at sub-hourly sampling rates, with K-Means clustering providing an additional 10% to 15% accuracy improvement [21]. However, reported findings indicate that validation for these federated architectures remains primarily simulation-based, with practical hardware-level deployment and resilience against model inversion under unbalanced data distributions representing ongoing implementation challenges [21].

4 Demand Response Strategy and Metaheuristic Appliance Scheduling Optimization

Residential demand-side management relies on automated Home Energy Management Systems that integrate advanced metering infrastructure, smart plugs, and intelligent control interfaces to coordinate appliance operations under dynamic demand response signals [4, 6, 22]. By monitoring real-time power profiles and shifting or curtailing deferrable loads, these architectures align residential power consumption with grid stability requirements while seeking to preserve occupant utility [6, 23]. Deployment studies demonstrate that coupling smart metering with rule-based or decisive control mechanisms enables autonomous load shedding and automated response to price-based demand response programs, eliminating the operational bottlenecks associated with manual consumer intervention [4, 23, 24].

To resolve the non-convex trade-offs between electricity cost minimization, peak-to-average ratio reduction, and consumer comfort constraints, metaheuristic and hybrid evolutionary algorithms are widely deployed for appliance scheduling [6, 24, 25]. Formulations combining multiple knapsack theory with heuristic search techniques, such as harmony search and enhanced differential evolution, provide structured frameworks for balancing household demand against available supply [25]. Hybrid algorithms frequently outperform standard single-algorithm baselines across simulated operational scenarios [24, 26, 27]. For instance, a hybrid genetic particle swarm optimization framework integrating photovoltaic generation and energy storage under real-time pricing achieved a 25.55% reduction in electricity costs, a 36.98% decrease in peak-to-average ratio, and a 24.02% reduction in carbon emissions compared to unscheduled baselines, outperforming genetic algorithms, binary particle swarm optimization, ant colony optimization, and bacterial foraging approaches [27]. Similarly, a hybrid algorithm combining genetic, particle swarm, and wind-driven optimization yielded a fitness cost of 19.34 (a 57.8% improvement over standard genetic algorithms), an optimal peak-to-average ratio of 10, carbon emissions of 3.41 tonnes/h, and a 79% decrease in grid import reliance under time-of-use pricing [26]. In dedicated wind-driven optimization models evaluated with a 5 kW rooftop photovoltaic installation, restricted time planning reduced daily electricity costs by 3.9% and peak-to-average ratio by 16.8% relative to constant-time planning, reaching a peak-to-average ratio of 1.0 and a net power demand of 0.8 kW under variable scheduling [28].

Scalability across multi-dwelling clusters and real-time responsiveness remain central challenges in scheduling optimization [29, 30]. In simulation and prototype assessments utilizing multi-objective mountain gazelle optimization under time-of-use tariffs, scheduling in a single dwelling without storage reduced electricity costs by 12.14% and peak-to-average ratio by 52.54%, with peak-hour electricity cost reductions reaching up to 80.15% [29]. When scaled to a cluster of 50 dwellings, the system recorded overall cost and peak-to-average ratio reductions of 11% and 74.68%, respectively, whereas adding photovoltaic and battery storage to a single dwelling yielded up to a 90% power cost reduction and an 89.13% improvement in user comfort index against a 12-year payback period [29]. Complementing heuristic scheduling, cloud-based priority-driven algorithms operating at 5-minute dispatch intervals resolve real-time trade-offs between instantaneous pricing and user comfort, achieving average cost savings of 40% under real-time pricing, 45% under time-of-use pricing, and 48% under critical peak pricing

[30]. Broader empirical and literature syntheses corroborate that advanced optimization methods, ranging from robust optimization in citizen energy communities to swarm techniques, deliver operational cost reductions spanning 11.4% for specific appliance deferrals up to 46.085% for swarm-based load management [31].

Tariff structures and regional socio-economic conditions significantly dictate the operational strategy and financial viability of home energy management systems [31, 32]. Under non-dynamic inclining block rate tariffs, where price signals are tied to cumulative consumption thresholds rather than specific hours, comfort zone-based load scheduling for high-draw appliances such as air conditioners offers substantial savings [32]. In an empirical case study of a 200 m2 residential household in Egypt, combining comfort zone optimization with rooftop photovoltaics and battery storage yielded an 81% bill reduction (annual savings of 33,374.6 EGP) and an estimated capital payback period of 0.68 years [32]. Scaled across 575,000 households in Greater Cairo, projected outcomes indicate efficiency gains of 0.90 TWh/year, solar offsets of 6.12 TWh/year, and 1.43 million tons of avoided annual carbon dioxide emissions [32]. However, the real-world performance of such systems remains constrained by behavioral unpredictability, long-term battery degradation, and solar intermittency, emphasizing the need for robust control architectures that accommodate physical storage limitations and stochastic occupant behavior across diverse pricing schemes [32].

5 Adaptive Reinforcement Learning and Multi-Agent Decision-Making Paradigms

Adaptive reinforcement learning frameworks address the stochasticity of residential demand by dynamically adjusting appliance schedules and energy resources without relying on explicit physical plant models. Multiobjective reinforcement learning formulations decouple competing operational priorities to accommodate fluctuating consumer preferences and pricing dynamics. An implementation utilizing dual Q-tables to separate electricity cost from user dissatisfaction demonstrated an 8.44% cost reduction relative to mixed-integer nonlinear programming in real-world evaluations under pricing and renewable generation uncertainty, while limiting average user dissatisfaction increases to 1.37% [33]. Similarly, Q-value reinforcement learning applied to home appliances scheduling with distributed photovoltaics and electrical energy storage establishes effective demand response actions and mitigates system uncertainty across bidirectional household-to-grid power flows [34]. For major thermal loads, deep reinforcement learning combined with dynamic setpoint adjustment achieved an average of 8% energy savings over rule-based control, rising to 16% during summer periods, while keeping temperatures outside comfort bounds for under 1% of operational time, shifting over 10% of flexible loads, and increasing renewable self-consumption by 9.5% [35].

To manage deep operational uncertainties in complex multi-source residential configurations, hybrid paradigms combine fuzzy logic, reinforcement learning, and metaheuristic optimization algorithms. A framework integrating mixed-integer linear programming with fuzzy reinforcement learning and metaheuristic search algorithms, including Harris Hawks Optimization and Wild Horse Optimization, handles outside temperature, solar irradiation, lighting load, and bidirectional vehicle-to-grid uncertainties via conditional value-at-risk formulations, achieving up to 53% in electricity expense savings in simulation while maintaining solution runtimes below 60 seconds [36]. In hybrid renewable energy systems encompassing solar, wind, battery storage, and electric vehicles, a fuzzy logic management system combined with reinforcement learning and the Starfish Optimization Algorithm achieved cost reductions of 35.2% under fixed tariffs, 23.8% under real-time pricing, and 26.43% under day-ahead pricing, while expanding renewable utilization up to 70% and lowering operating expenses and carbon emissions by 11.87% to 18.7% compared to diesel-based baselines [37].

Multi-agent reinforcement learning paradigms extend decision-making across distributed residential assets and multi-stakeholder interactions. Formulating multi-objective demand response as a multi-agent Markov decision process enables intelligent coordination among diverse Internet of Things devices, balancing trade-offs between electricity expenditures and occupant comfort [38]. Implementing a hierarchical Stackelberg game resolved through multi-agent deep deterministic policy gradient algorithms achieved a 30.41% reduction in total energy consumption, a 28.57% decrease in peak load, and improvements in system utility of 13.11% and 15.74% relative to baseline approaches in simulated IoT environments [39]. Furthermore, data-driven multi-objective deep reinforcement learning agents successfully bridge end-user objectives with distribution network constraints, co-optimizing appliance operations, storage, and electric vehicles against real-world data to simultaneously decrease consumer dissatisfaction, energy bills, and distribution transformer loss-of-life degradation [40].

6 Distributed Energy Resource Co-Optimization, Battery Health Preservation, and Transactive Markets

Holistic coordination of behind-the-meter distributed energy resources enables residential energy management systems to align local photovoltaic generation, battery energy storage systems, and electric vehicle charging with household appliance demands. In mathematical optimization frameworks, mixed-integer linear programming is frequently employed to resolve the operational scheduling of shiftable appliances, thermostatically controlled devices, and power-shiftable storage units [5, 41]. For example, integrating a fuzzy logic-based smart thermostat that dynamically adjusts temperature set-points based on solar radiation, electricity tariffs, and occupancy with a mixed-integer linear programming day-ahead scheduler achieved a 53.2% daily cost reduction and a 24% air-conditioning cost reduction in simulation under Turkish time-of-use tariffs [5]. Such models coordinate bidirectional power flows across residential storage, electric vehicles, and the distribution grid, creating operational pathways for vehicle-to-grid integration and self-consumption under dynamic tariff structures while preserving user comfort constraints [5, 41].

An essential design consideration in distributed storage operation is the explicit representation of battery degradation costs, as unconstrained price arbitrage often induces excessive cycling that shortens asset lifespan [5, 41, 42]. Integrating dedicated degradation models and capital replacement costs into scheduling formulations prevents uneconomic charge-discharge cycles, directly balancing economic arbitrage gains against physical battery longevity [5, 41, 42]. Beyond asset degradation, economic optimization alone can induce unintended environmental externalities [43]. An evaluation across 22 regions in the United States demonstrated that scheduling residential battery storage solely for electricity bill minimization increased household carbon dioxide emissions in 20 regions by 70 to 2200 kilograms annually, driven by storage round-trip inefficiencies and marginal generator fuel mixes [43]. However, implementing a multi-objective optimization framework evaluated at a social cost of carbon of 42 dollars per ton economically mitigated these emissions by 49 to 1450 kilograms of carbon dioxide per household annually [43].

At the neighborhood and distribution feeder scale, decentralized transactive energy architectures facilitate peer-to-peer energy trading while providing essential flexibility services to the grid [44, 45]. Multiagent coordination models allow residential buildings to schedule distributed resources locally and participate in real-time transactive markets, simultaneously preserving consumer privacy and eliminating reliance on centralized aggregators [44]. Simulation studies using Australian building data and tariff structures demonstrated that event-triggered transactive bidding incorporating storage degradation achieved 15% to 20% cost savings for consumers while relieving local transformer overloading at negligible cost relative to physical transformer upgrades [44]. To secure horizontal peer-to-peer and vertical grid-interactive transactions, blockchain architectures using tailored smart contracts and modified Practical Byzantine Fault Tolerance protocols have demonstrated practical feasibility on Internet of Things hardware [45]. In experimental evaluations, this blockchain framework recorded transaction latencies around 5 milliseconds, block confirmation times below 100 milliseconds, throughput reaching approximately 700 transactions per second, and a 25% overall cost reduction across horizontal and vertical markets, though scaling to large networks with tens of thousands of nodes requires further reduction in algorithmic complexity [45].

7 Cybersecurity, Zero Trust Protocols, and Privacy-Preserving Decentralized Governance

The expansion of smart home energy management systems introduces critical vulnerabilities across device interoperability, data privacy, and grid-connected infrastructure [46]. To mitigate these exposures, zero-trust architectures and edge-level network telemetry provide real-time verification and localized threat containment [47, 48]. Within edge monitoring frameworks, interpreting network telemetry such as domain name system queries and firewall logs on low-power hardware has demonstrated measurable security gains; in a six-week residential deployment, blocklist refinement improved domain name system blocking efficiency from 81.2% to 97.0% while decreasing virtual private network connection establishment times from approximately 3012 milliseconds to 2410 milliseconds [48]. In parallel, the POIZE framework implements zero-trust principles combined with data deduplication and lightweight anomaly detection using Random Forest classifiers, reducing redundant sensor data by approximately 50% during low-activity periods and 20% during daytime operation while maintaining an anomaly detection false positive rate of 4%, a false negative rate of 0.05, and a validation receiver operating characteristic area under the curve true positive rate of 0.938 [47]. However, the computational overhead of zero-trust verification introduces an average system overhead factor of 1.8 times compared to traditional architectures, underscoring the operational trade-offs of continuous perimeterless validation [47].

Securing resource-constrained Internet of Things hardware in residential environments requires lightweight cryptographic algorithms capable of operating within strict power and latency boundaries [49]. Experimental validation of the Triangle Based Security Algorithm on embedded development hardware demonstrated an encryption energy consumption of 0.20 microjoules per byte and an encryption latency of 0.007 milliseconds, outperforming standard cryptographic baselines such as Advanced Encryption Standard at 1.20 microjoules per byte, Data Encryption Standard at 2.08 microjoules per byte, and PAWN at 0.36 microjoules per byte and 0.0123 milliseconds [49]. Complementing low-level cryptographic protections, modular and interoperable architectures integrate standardized communication protocols and semantic web technologies to secure prosumer-oriented home automation systems and demand response operations, as validated in functional smart home test-bed implementations [50].

Protecting smart home infrastructure against malicious manipulation also requires targeted defenses against energy theft and unauthorized consumption tampering [51]. Multi-stage decision frameworks address this vulnerability by combining multi-model predictive forecasting, statistical filtering via simple moving averages, and secondary classification stages [51]. In simulated smart home environments, this hierarchical approach identified unauthorized consumption deviations with 99.96% detection accuracy without requiring dedicated hardware monitoring devices across all endpoints [51].

Decentralized governance models, including federated learning and blockchain smart contracts, enable collaborative optimization and demand-side management while keeping sensitive telemetry on local edge devices [52–54]. In spatio-temporal load forecasting across household consumer electronics, Split Federated Learning utilizing Gated Recurrent Units retains raw consumption data at the device layer, satisfying data privacy constraints while exceeding centralized baseline forecasting accuracy on the REDD, UK-DALE, and Pecan Street datasets [54]. When paired with fog-layer metaheuristic scheduling, this decentralized framework achieved an average reduction of 32% in total energy costs, a 51% decrease in user discomfort, a 40% reduction in peak-to-average ratio, and a 92% demand response compliance rate [54]. In community microgrids, game-theoretic scheduling integrated with blockchain architectures minimizes individual and community energy expenditure under dynamic electricity pricing without exposing private appliance usage patterns [52]. Similarly, combining edge-based predictive temperature control with blockchain-logged data handling and time-shifted processing reduced peak-time computational load by 22% and total energy consumption by 15.8% while maintaining indoor temperatures within 0.5 degrees Celsius [53].

Despite the algorithmic efficacy of decentralized security and privacy architectures, human factors and user perception present ongoing challenges to adoption [55]. User perception studies in residential Internet of Things environments indicate that consumer behaviors are predominantly driven by convenience and perceived direct benefit rather than rigorous privacy management [55]. Householders routinely place unverified trust in device manufacturers and remain largely unaware of privacy vulnerabilities arising from advanced inference algorithms operating on seemingly innocuous non-audio and non-visual sensor telemetry [55]. Addressing these behavioral gaps requires automated privacy-preserving frameworks, explainable artificial intelligence diagnostics, and standard security implementations that protect user data autonomously without requiring active technical oversight by consumers [47, 55].

8 Comparative Summary

Table 1: Comparative analysis of selected optimization and demand response frameworks for smart home energy management systems

Citation	**Optimization Method**	**Validation Setting**	**Reported Cost and Energy Savings**	**Reported Peak and Operational Impacts**
[39]	Hierarchical Stackelberg game with multiagent deep deterministic policy gradient (MADDPG)	Simulation of IoT-based smart home energy management system with varying appliance characteristics	Energy consumption: 30.41% reduction in overall energy consumption and 13.11% system utility increase	Peak load: 28.57% reduction in peak load
[33]	Multiobjective reinforcement learning (MORL) using dual Q-tables	Numerical analysis using real-world residential price and renewable generation data	Electricity cost: 8.44% cost reduction compared with mixed-integer nonlinear programming	User comfort: 1.37% average increase in user dissatisfaction level
[10]	Fog-based TinyML appliance classification using Decision Tree and Support Vector Machine	Hardware prototype with Raspberry Pi 3 Model B Rev 1.2 at 600 MHz and Zigbee smart plug/meter network	Daily power cost: 30.26% reduction in daily electricity cost (from 9.22 to 6.43 USD/day) under TOU	Classification latency: 1.59 microseconds (Decision Tree) and 23 ms (SVM) inference time
[5]	Two-stage framework combining fuzzy logic thermostat set-point control with MILP load scheduling	Simulation under Turkey Time-of-Use and feed-in tariff rate structures with BESS and EV integration	Daily electricity cost: 53.2% daily cost reduction under TOU and feed-in tariff rates	Appliance cost: 24% air-conditioning cost reduction compared to conventional thermostats
[36]	MILP with fuzzy reinforcement learning, CVaR risk management, and HHO/WHO metaheuristics	MATLAB simulation of residential loads, solar PV, BESS, and bidirectional EV under uncertain solar irradiation	Electricity expenses: Up to 53% savings in home electricity expenses	Computational time: Execution completed within 60 s
[27]	Heuristic programmable controller utilizing hybrid genetic particle swarm optimization (HGPO)	Simulation of residential smart home under real-time pricing with PV, ESS, and EV integration	Electricity cost: 25.55% reduction in electricity bills in PV and ESS scenario	PAR and emissions: 36.98% peak-to-average ratio reduction and 24.02% carbon emission reduction
[54]	Split Federated Learning with GRU forecasting and Fog-layer hybrid IGWO-TLBO metaheuristic	Empirical evaluation using REDD, UK-DALE, and Pecan Street residential datasets	Total energy cost: 32% average reduction in total energy cost	PAR and comfort: 40% peak-to-average ratio reduction and 51% decrease in user discomfort
[37]	Fuzzy-EMS enhanced with reinforcement learning and Starfish Optimization Algorithm (SFOA)	Hybrid renewable energy system simulation integrating solar PV, wind, BESS, and EV across fixed, RTP, and DAP pricing	Electricity cost: Reductions of 35.2% under fixed, 23.8% under RTP, and 26.43% under DAP pricing	Operating emissions: 11.87% to 18.7% reduction in operating costs and emissions relative to diesel baseline
[29]	Multi-objective mountain gazelle optimization (MMGO) algorithm	Prototype deployment and simulation spanning single dwelling and 50-dwelling cluster under TOU pricing	Electricity cost: 12.14% reduction for single dwelling (up to 90% with PV/BESS) and 11% for 50-dwelling cluster	PAR: 52.54% PAR reduction for single dwelling and 74.68% reduction for 50-dwelling cluster
[30]	Priority-driven stochastic real-time scheduling algorithm with cloud-connected smart plugs	Cloud infrastructure simulation evaluating 5-minute appliance dispatch under RTP, ToU, and CPP pricing	Electricity cost: Average potential cost savings of 40% (RTP), 45% (ToU), and 48% (CPP)	Not stated
[45]	Custom blockchain with modified PBFT consensus and distributed transactive energy trading algorithm	IoT hardware and simulation testbed with 5 to 10 prosumer smart homes executing P2P and grid transactions	User energy cost: 25% overall cost reduction (16% vertical grid DR and 11% horizontal P2P trading)	Transaction latency: 5 ms transaction delay and under 100 ms block confirmation time

The comparative analysis reveals substantial diversity in optimization methodologies, validation settings, and reported performance dimensions across smart home energy management implementations. Algorithmic approaches span classical mathematical formulations such as mixed-integer linear programming [5], heuristic and metaheuristic techniques [27, 29], multi-agent reinforcement learning [33, 39], hybrid intelligent systems [36, 37], and decentralized blockchain trading mechanisms [45]. Because these frameworks are validated across fundamentally disparate environments—ranging from purely simulated multi-appliance setups [27, 36, 39] and cloud infrastructure models [30] to numerical analyses with real-world traces [33], multi-dwelling cluster simulations [29], and physical hardware prototypes [10, 45]—direct cross-study ranking on a single performance scale is inherently limited. Instead, performance must be evaluated within specific metric families and operational assumptions.

Within the metric family of cost and energy savings, the reported reductions exhibit strong dependency on integrated distributed assets, tariff structures, and baseline comparisons. Mathematical programming and hybrid metaheuristic frameworks coupled with on-site storage and photovoltaics report significant economic savings under time-differentiated rate structures. For example, a two-stage fuzzy logic and mixed-integer linear programming scheduler achieved a 53.2% daily cost reduction under Turkish time-of-use and feed-in tariffs alongside a 24% air-conditioning expense reduction [5], while a robust mixed-integer formulation incorporating fuzzy reinforcement learning and metaheuristics achieved up to 53% in home electricity expense savings in simulation under solar irradiation uncertainty [36]. In multi-objective evolutionary applications, the multi-objective mountain gazelle optimization algorithm yielded a 12.14% cost reduction for a single dwelling without storage, which escalated to 90% when paired with local photovoltaic and battery storage systems under time-of-use pricing [29]. Similarly, priority-driven stochastic dispatch across cloud-connected smart plugs demonstrated average cost savings of 40% under real-time pricing, 45% under time-of-use pricing, and 48% under critical peak pricing [30], whereas transactive peer-to-peer and grid trading via custom blockchain protocols yielded a 25% overall user cost reduction [45].

Reported operational impacts, peak load adjustments, and user comfort metrics further illustrate critical engineering trade-offs inherent to residential scheduling. Peak-to-average ratio and peak load reductions range from 28.57% under hierarchical multi-agent deep deterministic policy gradient scheduling [39] and 36.98% under hybrid genetic particle swarm optimization [27] to 52.54% for single dwellings and 74.68% for 50-dwelling clusters under mountain gazelle optimization [29]. Decentralized frameworks also show substantial grid-relief capabilities; split federated learning paired with fog-layer metaheuristics achieved a 40% peak-to-average ratio reduction alongside a 51% decrease in user discomfort and a 32% average energy cost reduction [54]. Conversely, multiobjective reinforcement learning using dual Q-tables achieved an 8.44% cost reduction relative to mixed-integer nonlinear programming but incurred a 1.37% average increase in user dissatisfaction [33]. Operating emissions reductions relative to baseline configurations also vary across asset configurations, spanning 24.02% under hybrid evolutionary scheduling [27] and 11.87% to 18.7% under fuzzy reinforcement learning systems compared to diesel generation [37].

Hardware execution and latency metrics highlight distinct implementation boundaries between simulated models and physical edge deployments. In embedded prototype evaluations, a fog-based TinyML classifier executing on a Raspberry Pi 3 Model B achieved classification latencies of 1.59 microseconds with a decision tree and 23 milliseconds with a support vector machine, driving a 30.26% daily power cost reduction under time-of-use rates [10]. In decentralized transactive networks, a custom blockchain utilizing modified Practical Byzantine Fault Tolerance consensus achieved transaction latencies of 5 milliseconds and block confirmation times under 100 milliseconds across prosumer testbeds [45]. In simulation-based metaheuristic frameworks, computational runtimes remained bounded within 60 seconds for complex uncertainty scenarios [36]. Across the selected comparison entries, explicit operational and latency metrics remain unstated in several simulation-only studies [30], underscoring an ongoing gap between idealized algorithmic formulation and physical controller deployment under real-time hardware constraints.

9 Conclusion

The synthesized evidence demonstrates that smart home energy management systems can consistently lower residential electricity expenditures, shave peak demand, and improve self-consumption of on-site distributed energy resources. Tiered edge-fog-cloud architectures provide effective structural partitioning, enabling localized sensing and rapid appliance actuation while offloading heavy forecasting and optimization workloads to intermediary or cloud nodes. Algorithmic formulations—including mixed-integer linear programming, hybrid metaheuristics, multi-agent reinforcement learning, and federated learning—demonstrate high efficacy across simulated environments and selected hardware prototypes. Furthermore, integrating dedicated battery degradation models and multi-objective emissions accounting proves essential to prevent premature storage asset retirement and unintended environmental externalities driven by unconstrained price arbitrage.

Nevertheless, substantial uncertainties remain across the reviewed literature. Most advanced optimization frameworks remain validated primarily within idealized simulation environments, single-household testbeds, or limited time-horizon evaluations. Crucial deployment-level variables—such as non-stationary occupant behavior, stochastic appliance usage, multi-vendor device interoperability, hardware-constrained inference latency, and the computational overhead of zero-trust security verification—are infrequently evaluated in cohesive, long-term field studies. Moreover, while decentralized frameworks such as federated learning and blockchain-based transactive trading offer robust data privacy and security guarantees, their real-time transaction throughput, communication overhead, and resilience against adversarial data poisoning under extreme network scaling require rigorous physical validation. Resolving these uncertainties will require standardized multi-dwelling field testbeds, uniform benchmarking protocols that simultaneously track economic, comfort, physical degradation, and latency metrics, and human-in-the-loop validation under dynamic socio-technical conditions.

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