Architectural Patterns, Operational Optimization, and Cyber-Physical Security in Smart Home Energy Management Systems: A Systematic Review

Abstract

Smart home energy management systems serve as critical operational hubs for coordinating residential distributed energy resources, flexible appliance scheduling, and demand response participation. However, realizing efficient and resilient residential energy control requires navigating complex trade-offs among legacy hardware retrofitting, dynamic multi-objective optimization, and evolving cyber-physical security risks. This review synthesizes selected evidence across physical edge retrofits, predictive load forecasting, mathematical and reinforcement learning optimization, telemetry threat mitigation, and decentralized transactive architectures. The reviewed literature demonstrates that low-cost microcontroller retrofits and embedded edge intelligence can effectively incorporate non-communicating appliances and disaggregate household loads, while mathematical programming, metaheuristics, and deep reinforcement learning deliver substantial reductions in operating costs and peak-to-average ratios. Concurrently, federated learning and distributed ledger frameworks offer privacy-preserving, trust-minimized transactive coordination, though they introduce measurable computational, throughput, and synchronization overheads on constrained residential hardware. By examining operational outcomes across diverse simulation platforms, dataset benchmarks, and single-board hardware testbeds, this synthesis highlights persistent tensions between predictive fidelity and edge execution constraints, outlining open research challenges essential for deploying scalable, cyber-resilient residential energy management systems.

Contents

1 Introduction

The decarbonization and decentralization of residential power grids have transformed smart home energy management systems from isolated monitoring tools into dynamic, closed-loop control architectures [1, 2]. Modern residential controllers must balance volatile tariff structures, local photovoltaic generation, electrochemical storage degradation, and occupant thermal comfort while coordinating complex domestic loads [3, 4]. Achieving these operational objectives requires overcoming substantial physical and computational challenges, notably integrating legacy appliances without expensive infrastructure overhauls, maintaining real-time control under strict computational budgets, and protecting communication interfaces against malicious telemetry manipulation [5, 6].

Methodological approaches across the literature encompass a wide spectrum of analytical and data-driven paradigms, ranging from mixed-integer linear programming and multi-agent deep reinforcement learning to physics-informed digital twins and decentralized blockchain ledgers [7–9]. While advanced optimization and predictive models demonstrate high efficacy in controlled simulation settings, deploying these algorithms to physical edge infrastructure exposes operational bottlenecks related to processor limitations, memory consumption, inference latency, and protocol interoperability [10–12]. Furthermore, mitigating cyber-physical threat vectors such as false data injection and energy theft introduces additional computational overhead that can constrain real-time responsiveness [13, 14].

This review synthesizes selected evidence concerning architectural patterns, operational optimization strategies, cyber-physical security mechanisms, and decentralized privacy frameworks in smart home energy management systems. The scope of this analysis is defined by the evaluated empirical datasets, prototype testbeds, and numerical modeling environments reported in the reviewed literature. It does not claim exhaustive coverage of municipal-scale distribution grids or commercial building automation systems, focusing instead on the design trade-offs, empirical limitations, and structural tensions governing residential-scale energy management.

2 Edge Sensing, Middleware Architectures, and Hardware Retrofitting for Heterogeneous Appliance Networks

A central challenge in residential energy management is incorporating legacy, non-communicating appliances into modern control environments without necessitating full device replacement. To bridge this gap, hardware retrofitting frameworks employ low-cost intermediary controllers and protocol translation layers. Intermediary controller architectures, such as the Homergy system, utilize microcontroller platforms with opto-coupled relays and Wi-Fi modules to integrate both legacy and connected appliances into an IoT ecosystem, demonstrating weekly energy savings across distinct residential and office deployment profiles [5, 15]. Similarly, custom microcontroller-based smart meters incorporating prioritization algorithms enable automated load switching and peak-to-average ratio reduction without expensive infrastructure overhauls [16]. Beyond discrete appliance switching, low-cost microcontrollers can provide indirect control mechanisms for residential energy assets; for instance, an ESP32-based controller can manipulate wattmeter readings and communicate over Modbus to govern commercial solar inverters and battery energy storage systems, permitting grid injection and flexibility market participation without internal inverter modifications [17]. In localized deployment contexts with tiered tariffs, low-cost minimal-hardware prototypes have similarly combined comfort-constrained scheduling with photovoltaic and battery assets to achieve rapid economic payback [18].

To balance sensing fidelity with installation complexity, edge-based data acquisition paradigms increasingly combine physical metering with embedded machine learning and Non-Intrusive Appliance Load Monitoring (NILM). Rather than deploying dedicated power meters across every individual load, fog and edge architectures deploy cognitive gateways to run non-intrusive disaggregation. The integration of multi-stage artificial neural network load monitoring within Tridium Niagara framework gateways exemplifies how fog-cloud partitioning can extract individual appliance activities from aggregated power streams [19]. Complementing neural approaches, edge-capable middleware using microservices and Wi-SUN protocols has demonstrated the feasibility of applying principal component analysis on aggregated meter data sampled at 1/5 Hz to disaggregate active appliance states [20]. Furthermore, IoT platforms incorporating NILM provide local host interfaces to coordinate automated load scheduling against regional tariff structures [21]. Where discrete device-level sensing remains necessary, TinyML implementations deployed on single-board edge devices classify appliance signatures from smart plug telemetry; in an experimental setup, decision tree classifiers operating on a 600 MHz processor achieved microsecond-scale inference and 100% accuracy, while support vector machines operated with 23-millisecond latency and 97% accuracy, supporting automated time-of-use demand response [11]. Such embedded tracking and predictive analytics provide the continuous telemetry needed to reduce system losses and guide automated load shifting [22].

Managing heterogeneous device networks requires open, secure middleware architectures capable of unifying disparate physical interfaces and standardized communication protocols [23]. Modular architectures address multi-vendor interoperability by integrating semantic web technologies and standard data communication interfaces directly with legacy home automation systems, providing verified functional modularity and security within smart home test-beds [24]. At the grid interaction interface, integrating standardized demand-response frameworks—such as OpenADR 2.0b Virtual End Nodes coupled with Bluetooth Low Energy sensor networks—has been demonstrated in field deployments across 24 public housing units over 12 months, achieving an average household energy reduction of 12.62 percent alongside multi-kilowatt load shedding during peak grid events [25]. Middleware layers also support commercial and multi-site demand-side automation, where custom IoT meters and centralized middleware coordinate isolated breaker-level automated control of high-demand HVAC units across operational facilities [26]. Complementary consumer-facing implementations leverage standardized application ecosystems and smart plugs to automate demand response and monitor real-time consumption [27]. Across these approaches, effective system execution relies on co-designing low-cost edge controllers, lightweight load classification, and standardized communication middleware to manage diverse appliance networks.

3 Predictive Load Analytics, Physics-Informed Modeling, and Digital Twins at the Computational Edge

Data-driven load forecasting and sensor instrumentation represent critical foundational layers for residential energy management systems. Sensing architectures utilizing Internet of Things hardware, such as microcontroller units interfaced with power monitoring modules, facilitate real-time acquisition of electrical parameters including voltage, current, active power, frequency, and power factor for short-term prediction [28]. When evaluating algorithmic options on residential datasets from multiple load zones, ensemble learning techniques such as random forest have demonstrated lower average forecasting errors, reaching a root mean square error of 0.060 09, compared to recurrent neural architectures such as gated recurrent units at 0.062 75 and bidirectional long short-term memory networks at 0.063 15 [28]. However, localized deployment of these predictive pipelines is often shaped by the processing limitations of existing residential infrastructure, where edge devices typically operate with modest central processing units and minimal random-access memory [29]. Evaluating day-ahead forecasting across household demand, heat pump consumption, and photovoltaic generation shows clear operational trade-offs across model families: stochastic gradient descent regressors provide superior execution speeds, Kolmogorov-Arnold networks achieve lower root mean square error metrics, and tree-based gradient boosting models show particular strength in capturing peak demand patterns [29].

Digital twin paradigms extend these predictive capabilities by maintaining synchronized virtual representations of physical assets to guide real-time scheduling and control. Integrating long short-term memory forecasting within an edge-based digital twin home energy management framework enables dynamic tracking of photovoltaic generation, electric vehicle availability, and appliance demand, yielding operational cost savings of up to 10% under simulated 15-minute scheduling intervals [30]. To balance physical system behavior with complex data dynamics, hybrid physics-informed neural network digital twins have been coupled with deep reinforcement learning and blockchain security layers for smart building control [8]. Within smart building evaluations, this hybrid framework achieved a mean absolute error of 0.2369 kWh, a root mean square error of 0.2980 kWh, a mean bias error of 0.0296 kWh, and an R-squared coefficient of 0.9895, translating to a 0.5 s response time, a 35% reduction in energy costs, a 96% user comfort index, and a 40% renewable energy utilization rate [8].

Despite the operational and predictive gains reported across digital twin and machine learning architectures, significant computational and structural bottlenecks remain at the computational edge. Advanced physics-informed and hybrid digital twin systems demand substantial computational resources during initial model training, which can impede real-time training and adaptation on low-resource residential hardware [8]. Furthermore, these frameworks depend heavily on consistent, high-resolution telemetry from smart meters and connected sensors, and they encounter substantial scaling barriers when expanding from individual residential dwellings to broader municipal networks characterized by heightened data heterogeneity [8]. Resolving the balance between predictive fidelity, execution runtime, and memory overhead thus remains an essential requirement for migrating advanced forecasting and digital twin capabilities directly onto edge-level residential controllers [29, 30].

4 Deterministic, Stochastic, and Metaheuristic Scheduling under Physical Degradation and Multi-Source Uncertainty

Mathematical programming paradigms provide rigorous analytical formulations for scheduling residential energy consumption while addressing multi-source uncertainties and user preferences. A prominent approach integrates stochastic and robust programming within a mixed-integer linear programming formulation to simultaneously manage market price volatility via budgeted robust optimization and capture weather-driven renewable and demand variability through scenario-based stochastic methods [4]. Evaluated via the augmented epsilon-constraint method, this hybrid stochastic-robust model achieved a 47% reduction in daily operating costs and a 50% mitigation in grid-based peak-to-average ratio relative to unmanaged baselines, while conditional value-at-risk mechanisms reduced worst-case user thermal discomfort by 43% [4]. Beyond pure mathematical optimization, broader reviews of home energy management architectures underscore that operational controllers must consistently balance economic objectives, environmental factors, load profiles, and consumer comfort under dynamic demand response programs [2].

Incorporating physical degradation dynamics into mathematical scheduling models is critical for mitigating the long-term capital depreciation of electrochemical storage assets. Standard demand management that encourages high-frequency charging and discharging can accelerate battery aging; consequently, integrating explicit degradation models into scheduling frameworks coordinates appliances and storage to curb energy expenses while safeguarding cell longevity [31]. Dedicated mixed-integer linear programming formulations address this trade-off by explicitly factoring in capital replacement costs for stationary energy storage systems and electric vehicles, thereby prolonging battery lifetime while pursuing cost minimization and user preferences [32]. Similarly, two-stage architectures combine mixed-integer linear programming with battery degradation constraints to prevent uneconomic energy arbitrage across bi-directional power flows between homes, battery systems, electric vehicles, and the grid, realizing a 53.2% daily cost reduction under time-of-use and feed-in tariff structures [3].

Fuzzy inference systems offer an effective mechanism for managing non-linear comfort variables and environmental uncertainty without imposing excessive computational overhead on embedded hardware. In two-stage energy management designs, fuzzy logic modules can dynamically fuzzify electricity tariffs, solar irradiance, and occupant presence to establish time-varying thermostat set-points, which are subsequently passed to a mixed-integer linear programming scheduler to lower air-conditioning operational costs by 24% relative to fixed-set-point baselines [3]. Standalone fuzzy inference systems that incorporate ambient relative humidity and indoor temperature feedback can automatically maintain thermal comfort while reducing energy consumption by 28% in resource-constrained operating systems suitable for low-power smart sensors [33]. Comprehensive surveys confirm that fuzzy logic and adaptive neuro-fuzzy inference systems remain widely investigated alternatives to conventional deterministic controllers for handling environmental fuzziness and occupant behavior [2].

Metaheuristic and hybrid evolutionary algorithms are widely employed to resolve complex, non-convex appliance scheduling problems across diverse pricing tariffs. In microgrid settings with distributed solar and wind generation, intelligent load controllers reduce peak demand and energy expenditure by shifting flexible appliance loads to lower-tariff periods [34]. Hybrid optimization techniques combine distinct heuristic search mechanisms to balance exploration and exploitation; for instance, a hybrid combining genetic algorithms, particle swarm optimization, and wind-driven optimization achieved a 57.8% fitness cost improvement over standard genetic algorithms alongside a 79% reduction in grid import dependency under time-of-use pricing [35]. Similarly, hybridizing wind-driven optimization with bacterial foraging optimization has demonstrated reductions in peak-to-average ratio and electricity expenses while maintaining user comfort when responding to automated demand response signals [36]. When benchmarked against differential evolution across variable time planning with rooftop photovoltaics, wind-driven optimization achieved an optimal peak-to-average ratio of 1 and lower net daily energy costs [37]. Particle swarm optimization has also shown efficacy in minimizing residential consumption costs and stabilizing the peak-to-average ratio under combined real-time and inclined block rate pricing [38], while hybrid data-driven frameworks pairing forensic-based investigation algorithms with isolation forests have been implemented within simulated multi-source microgrids to balance energy costs and user satisfaction [39].

5 Multi-Agent and Deep Reinforcement Learning for Adaptive Demand Response and Grid-Interactive Flexibility

Adaptive demand response in smart home energy management requires decision frameworks capable of balancing volatile electricity prices, fluctuating user comfort, and hardware constraints. Multi-agent deep reinforcement learning and game-theoretic architectures have emerged as principal mechanisms to coordinate heterogeneous home appliances. Formulating home energy management as a Markov decision process allows multi-agent deep reinforcement learning algorithms to simultaneously minimize electricity expenditure and maximize resident comfort within Internet of Things environments [40]. To resolve hierarchical control conflicts between aggregators and end users, game-theoretic formulations provide structured coordination; for instance, a hierarchical Stackelberg game-based incentive structure solved via multi-agent deep deterministic policy gradient algorithms reduced overall energy consumption by 30.41% and peak load by 28.57% while improving system utility by 13.11% and 15.74% over compared benchmark schemes in simulation [7].

To manage complex search spaces and fluctuating renewable generation, several strategies combine reinforcement learning with metaheuristic or fuzzy optimization techniques. Tabular Q-learning approaches incorporate end-user priorities and bidirectional home-to-grid energy flows alongside photovoltaic and electrical energy storage systems to lower electricity costs and reduce system uncertainty during appliance scheduling [41]. For hybrid renewable energy systems combining solar photovoltaics, wind turbines, battery storage, and electric vehicles, a fuzzy logic-based energy management system optimized via the Starfish Optimization Algorithm and reinforced with learning mechanisms achieved simulation cost reductions of 35.2% under fixed pricing, 23.8% under real-time pricing, and 26.43% under day-ahead pricing, while cutting operating costs and carbon emissions by 11.87% to 18.7% relative to diesel-based systems in MATLAB evaluations [42]. Similarly, integrating a self-adaptive puma optimizer with a multi-objective deep Q-network for dynamic appliance scheduling lowered the peak-to-average ratio from 3.4286 to 1.9765 without renewable energy sources and to 1.0339 with renewable generation in MATLAB simulations [43].

Beyond individual household economics, advanced reinforcement learning and stochastic scheduling architectures increasingly incorporate grid-interactive flexibility and distribution-level asset preservation. Decentralized clustering of smart home microgrids coordinated with power distribution networks using multi-objective cheetah optimization demonstrated peak load reductions of 36% to 44% across deterministic and uncertain case studies, maintaining user comfort levels above 60% while improving voltage profiles and network losses [44]. At the localized equipment level, deep reinforcement learning agents evaluated on real-world data have incorporated distribution transformer loading conditions and transformer loss-of-life metrics alongside resident dissatisfaction costs and energy bills when scheduling household loads, storage, photovoltaics, and electric vehicle charging [45]. These reported findings indicate that multi-objective reinforcement learning and metaheuristic coordination can mitigate grid-side stress while adapting to dynamic consumer preferences.

6 Cyber-Resilience, Intrusion Detection, and Zero-Trust Architectures in Residential Energy Infrastructure

The integration of consumer Internet of Things devices and smart appliances into demand-side response mechanisms expands the cyber-attack surface of residential energy infrastructure [1]. As smart grid deployments increasingly incorporate big data processing and machine learning pipelines, vulnerabilities in communication interfaces introduce significant operational and privacy risks [6]. Mitigating these vulnerabilities requires structured protections across system architectures, distribution networks, device-level product assurance, and consumer operational practices [1].

To counter telemetry manipulation such as false data injection attacks, machine learning frameworks have been adapted for individual load forecasting and anomaly detection [14]. In an evaluation using five months of empirical telemetry from 2,089 smart meters, combining K-Means clustering with neural network forecasting reduced the mean absolute scaled percentage error by up to 25.6% and decreased computational runtime from days to minutes across autoregressive integrated moving average, conditional inference tree, multilayer perceptron, and neural network autoregression models [14]. When coupled with a Principal Component Analysis-based One-Class Support Vector Machine to detect synthetic scaling, ramping, and random cyberattacks across half of the telemetry records, the anomaly detection scheme achieved 99.3% overall accuracy, 100% sensitivity, 98.62% precision, 98.6% specificity, and an F1-score of 0.9896, while maintaining 100% accuracy on non-manipulated data [14].

Energy theft presents another distinct threat vector in residential smart metering environments where auxiliary physical monitoring devices may be absent [13]. Addressing this constraint, the Smart Energy Theft System employs a three-stage analytical workflow comprising a multimodel machine learning forecasting stage for baseline power estimation, a primary filtering stage utilizing a simple moving average, and a secondary module for final theft determination [13]. In simulated smart home environments, this multi-stage inference pipeline achieved an energy theft detection accuracy of 99.96% without requiring dedicated external sensor installations [13].

Zero-trust principles have also been explored to enforce continuous authentication and anomaly mitigation directly within smart home networks [10]. The POIZE framework integrates Zero Trust Architecture with TinyML anomaly detection, explainable artificial intelligence, data filtering, and de-duplication [10]. In simulated IoT and edge node environments, its Random Forest classification model achieved area under the receiver operating characteristic curve values of 0.958 during training, 0.95 during testing, and 0.938 during validation, corresponding to a false positive rate of 4% and a false negative rate of 0.05 [10]. Data de-duplication lowered transmission volumes by roughly 50% during low-activity intervals and by approximately 20% during daytime operation, though the combined security and inference pipeline introduced an average throughput overhead of a factor of 1.8x compared to an unhardened baseline [10]. Practical deployment remains constrained by device heterogeneity across commercial vendors and heightened latency during peak telemetry events [10].

At the constrained device and wireless sensor layer, specialized cryptographic algorithms provide data integrity and confidentiality under tight energy budgets [46]. The Triangle Based Security Algorithm, evaluated on an embedded platform comprising an Intel Galileo board, temperature sensor, and wireless module, exhibited an energy consumption profile of 0.20 Micro Joule/Byte [46]. This measured energy footprint was lower than established hash functions such as MD4 (0.52 Micro Joule/Byte), MD5 (0.59 Micro Joule/Byte), SHA-1 (0.76 Micro Joule/Byte), and HMAC (1.16 Micro Joule/Byte); symmetric ciphers such as RC4 (0.49 Micro Joule/Byte), Blowfish (0.81 Micro Joule/Byte), AES (1.2 Micro Joule/Byte), and DES (2.08 Micro Joule/Byte); and specialized wireless sensor network protocols including PAWN (0.36 Micro Joule/Byte), PRESENT-GRP (0.47 Micro Joule/Byte), and Alarm-Net (0.53 Micro Joule/Byte) [46].

7 Privacy-Preserving Transactive Energy Systems: Federated Learning and Distributed Ledger Consensus

Decentralized transactive energy architectures increasingly rely on federated learning to balance localized demand management with user privacy preservation. By decoupling model training from raw data centralization, federated paradigms mitigate consumer privacy risks across heterogeneous Internet of Things devices. In spatiotemporal load forecasting and appliance scheduling, a split federated learning framework integrating Gated Recurrent Units with fog-layer metaheuristic optimization on datasets including REDD, UK-DALE, and Pecan Street achieved a 32% reduction in total energy costs, a 51% reduction in user discomfort, a 40% decrease in peak-to-average ratio, and a 92% demand response compliance rate while outperforming centralized predictive baselines [12]. For thermal and cost co-optimization, personalized federated reinforcement learning combining Moreau envelopes with Twin-Delayed Deep Deterministic Policy Gradient models demonstrated faster convergence and higher overall reward than standard federated averaging or proximal baselines, yielding an approximate 10% energy cost reduction while constraining indoor temperature deviations within 1.5 degrees Celsius [47]. To guard against model inference attacks without sacrificing forecasting fidelity, federated learning architectures integrated with dual-layer blockchain logging and server-side Gaussian differential privacy achieved a Mean Absolute Error of 0.153 and a Mean Absolute Percentage Error of 0.085 when evaluated on the PRECON household electricity consumption dataset using Random Forest estimators [48]. Furthermore, cross-paradigm evaluations indicate that federated learning models can reach 95% of the accuracy achieved by centralized deep learning systems in smart energy consumption forecasting [49].

Complementing privacy-preserving learning mechanisms, distributed ledger frameworks and self-enforcing smart contracts provide transparent, trust-minimized coordination for demand response programs and peer-to-peer energy trading. Non-cooperative game-theoretic appliance scheduling models integrated with Ethereum smart contracts deployed via Solidity enable autonomous billing and monitoring in community microgrids while preserving user privacy [50]. In flexibility markets, Ethereum-based ledgers storing tamper-proof prosumption information allow automated verification of demand response signals and execution of financial settlements, improving grid balancing accuracy while reducing the required flexibility convergence volume [51]. For transactive exchange mechanisms, permissioned Hyperledger Fabric implementations for peer-to-peer trading have demonstrated average transaction latencies of 1.2 seconds, smart contract execution success rates of 98.7%, and an additional 12% cost savings for households trading surplus renewable generation [49]. Similarly, transactive management combining grid-level vertical coordination and peer-to-peer horizontal trading decomposed via the alternating direction method of multipliers achieved a 25% overall cost reduction across simulated multi-user scenarios [9].

Despite these operational benefits, the integration of distributed ledger consensus and decentralized intelligence introduces tangible computational, latency, and scalability overheads across resource-constrained smart home hardware. Prototype deployments of predictive temperature management coupling edge computing with blockchain ledgers achieved a 15.8% reduction in energy consumption and a 22% decrease in peak computational load, maintaining temperature stability within plus or minus 0.5 degrees Celsius and a 5-minute response time compared to traditional control baselines [52]. However, reliability for specific physical events remained variable, exhibiting a 28.5% success rate for radiator heating activation, 37.3% for cooling detection, and 68.4% for scheduled heating events, while highlighting scalability constraints across broader sensor networks [52]. Consensus performance on physical edge infrastructure shows that lightweight adaptations, such as a modified Practical Byzantine Fault Tolerance protocol tested on an 11-node Raspberry Pi network, can sustain peak throughputs around 700 transactions per second with 5-millisecond transaction delays and sub-100-millisecond block confirmation times under moderate node resource consumption of 480 megabytes of memory and below 50% central processing unit utilization [9]. Nonetheless, communication overhead, model synchronization delays in federated loops, and high computational complexity when scaling distributed consensus to massive IoT networks encompassing tens of thousands of nodes remain critical constraints in contemporary decentralized energy systems [9, 49, 52].

8 Comparative Summary

Table 1: Comparison of control strategies, validation environments, and demand-side performance metrics in selected smart home energy management systems.

Citation	Control and Optimization Method	Validation Setting	Reported Cost or Energy Reduction	Reported Peak or Demand Effect
[7]	Stackelberg game with multi-agent deep deterministic policy gradient	IoT-based SHEMS simulation model	Energy consumption: 30.41% reduction vs benchmark schemes	Peak load: 28.57% reduction
[11]	TinyML classifiers on smart meter with Zigbee smart plugs	Raspberry Pi 3 Model B hardware testbed under TOU pricing	Electricity cost: 30.26% reduction (from 9.22 to 6.43 USD/day)	Not stated
[3]	MILP day-ahead scheduling integrated with fuzzy logic thermostat	Household simulation under TOU and feed-in tariff tariffs in Turkey	Electricity cost: 53.2% daily cost reduction (24% AC cost reduction)	Not stated
[8]	Hybrid physics-informed neural networks and digital twin with DRL	Smart building and smart grid simulation environment	Energy cost: 35% reduction	Not stated
[12]	Split federated learning GRU with hybrid IGWO-TLBO algorithm	REDD, UK-DALE, and Pecan Street residential datasets	Energy cost: 32% average reduction in total cost	Peak-to-average ratio: 40% reduction
[4]	Hybrid stochastic-robust MILP with Conditional Value-at-Risk	Numerical experiments with price and renewable generation uncertainties	Operating cost: 47% reduction in daily operating costs	Peak-to-average ratio: 50% mitigation
[9]	Blockchain smart contracts with distributed ADMM optimization	Test network of 11 Raspberry Pis with 5-to-10 user simulation	Overall user cost: 25% reduction across transactive markets	Not stated

The evaluated smart home energy management systems leverage diverse control and optimization frameworks, spanning game-theoretic deep reinforcement learning [7], embedded TinyML classifiers [11], mixed-integer linear programming with fuzzy logic set-point regulation [3], hybrid physics-informed neural network digital twins [8], split federated learning [12], robust stochastic programming [4], and distributed alternating direction method of multipliers coordination executed via blockchain smart contracts [9]. A clear division is evident across validation environments: mathematical scheduling formulations and game-theoretic models are predominantly evaluated within numerical experiments and domain simulations [3, 4, 7, 8], whereas federated learning approaches utilize multi-dwelling residential telemetry datasets [12], and lightweight classification or distributed transactive mechanisms are validated directly on physical single-board computing testbeds [9, 11].

Direct performance comparisons across systems are constrained by differing baseline configurations, local tariff mechanisms, and reported metric families. Within the reported cost reduction dimensions, realized savings range from 25% overall user cost reduction in simulated transactive microgrids [9] to a 53.2% daily cost reduction under time-of-use and feed-in tariffs in household simulations [3]. Intermediate financial outcomes include a 30.26% daily electricity cost reduction on physical smart meter hardware [11], a 32% average total cost reduction across residential datasets [12], a 35% energy cost reduction in digital twin environments [8], and a 47% daily operating cost reduction under stochastic-robust programming [4]. Where energy consumption rather than financial expenditure was evaluated, multi-agent policy gradients demonstrated a 30.41% reduction relative to benchmark schemes [7].

Reporting of demand-side grid impact metrics remains selective across the evaluated literature, with several implementations omitting peak load or peak-to-average ratio measurements entirely [3, 8, 9, 11]. Among systems reporting grid-smoothing performance, hybrid stochastic-robust optimization incorporating conditional value-at-risk achieved a 50% peak-to-average ratio mitigation [4], while split federated gated recurrent units combined with metaheuristics yielded a 40% peak-to-average ratio reduction on empirical datasets [12]. In a dedicated Internet of Things simulation model, game-theoretic multi-agent reinforcement learning achieved a 28.57% reduction in absolute peak load [7]. These findings indicate that while significant demand-flattening capabilities exist across disparate optimization families, comprehensive grid-side evaluation is inconsistently incorporated alongside consumer-centric cost metrics.

9 Conclusion

The synthesized evidence indicates that smart home energy management systems can effectively reconcile consumer economic objectives with demand-side flexibility when appropriate control architectures are matched to operational constraints. Low-cost edge retrofits and non-intrusive load monitoring reliably bridge legacy appliances into modern control environments without full hardware replacement. Furthermore, mathematical programming, fuzzy inference, metaheuristics, and reinforcement learning consistently demonstrate substantial cost savings, thermal comfort maintenance, and peak-to-average ratio reductions across varied pricing tariffs. In the security domain, machine learning-driven anomaly detection and lightweight cryptographic primitives provide high detection accuracy against false data injection and energy theft under constrained energy budgets.

Nevertheless, significant uncertainties persist regarding the scalability, physical execution reliability, and long-term stability of advanced control architectures on resource-constrained residential hardware. High-fidelity digital twins and complex physics-informed models encounter severe memory and computational bottlenecks on embedded processors, while zero-trust and decentralized blockchain consensus frameworks introduce measurable throughput and latency penalties. Additionally, physical prototype deployments reveal variable actuation success rates across real-world environmental events, and federated learning workflows face synchronization delays across heterogeneous communication networks.

Resolving these uncertainties will require multi-season empirical field trials that simultaneously evaluate optimization fidelity, hardware degradation, and cyber-physical defense mechanisms on unified, open-source residential testbeds. Future research must also establish standardized cross-domain benchmarking protocols that report consistent energy, economic, comfort, and grid-interaction metrics across diverse climate zones, housing typologies, and tariff structures.

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