Smart Home Energy Management System

1 Executive Summary

Residential energy demand represents a major fraction of global energy consumption, driven primarily by space conditioning, water heating, and home appliances. While smart home energy management systems and demand-side response provide pathways for operational flexibility, existing scheduling paradigms face substantial technical trade-offs. Prior residential battery scheduling models focusing solely on dynamic price minimization have been shown to exacerbate distribution transformer loading and battery degradation, while advanced black-box machine learning controllers often lack the interpretability required for user trust and consistent operational oversight. This project addresses these challenges by developing and validating an integrated, edge-aware smart home energy management controller designed to dynamically schedule residential flexible appliances, energy storage, and solar generation under time-varying tariff structures while maintaining occupant comfort boundaries. The proposed technical framework deploys a modular and interoperable device interface layer using standardized edge middleware to achieve low-latency appliance recognition and automated demand-response dispatch. To resolve multi-criteria trade-offs, the supervisory core implements hierarchical-stochastic model predictive control that simultaneously minimizes electricity expenditures, restricts peak-to-average load ratios, and mitigates battery degradation and distribution transformer stress. An interpretable forecasting module couples predictive building thermal modeling with renewable generation estimation to ensure robust control execution under solar intermittency and operational uncertainties. The expected value encompasses automated utility cost savings, improved photovoltaic self-consumption, and reliable indoor climate control for residential prosumers, alongside reduced peak feeder stress and enhanced grid hosting capacity for distribution networks. Execution readiness is grounded in a sequential four-phase progression moving from hardware requirements definition and control formulation through controller-hardware-in-the-loop simulation benchmarking to experimental prototype testbed validation, supported by proven solver architectures and deterministic fail-safe fallback mechanisms.

2 Problem, Context, and Rationale

Building energy consumption accounts for 30 to 45 percent of global energy use, with residential demand driven primarily by home appliances, water heating, and space heating [1]. To mitigate these massive energy demands and support grid reliability, home energy management systems have emerged as critical infrastructures connecting residential devices, communication networks, and smart grid demand response applications [2]. In parallel, the increasing reliance on demand-side response to provide cost-effective grid flexibility has accelerated the adoption of artificial intelligence and machine learning techniques, which enable near real-time operational decisions, dynamic pricing adaptation, and device scheduling across complex consumer environments [3].

However, the reviewed literature reveals key technical challenges in current optimization and control paradigms. In residential battery energy storage scheduling under dynamic electricity pricing, optimizing purely for financial cost reduction has been shown to increase household carbon dioxide emissions in 20 of 22 analyzed regions in the United States, generating annual emission increases between 70 and 2200 kg per household due to grid marginal generation fuel mixes and storage inefficiencies [4]. Although multi-objective formulations incorporating emissions costs can mitigate these impacts, simultaneously managing cost, emissions, and appliance flexibility remains complex [4]. Concurrently, the deployment of machine learning in building energy management is constrained by the black-box nature of advanced models, where prevalent explanation tools such as SHAP and LIME provide only limited interpretability, hindering end-user trust and consistent evaluation across operational tasks [5].

Addressing these challenges requires an energy management framework that integrates multi-objective optimization with interpretable decision-making mechanisms. By resolving the conflict between cost minimization and emissions abatement while addressing the interpretability limitations identified in prior machine learning applications [4, 5], the proposed intervention establishes a rigorous foundation for sustainable and trustworthy residential energy management. The specific methodological architecture, novelty arguments, and empirical evaluation strategies designed to achieve these objectives are detailed in the subsequent sections of this proposal.

3 Objectives and Success Criteria

The primary objective of this project is to develop and validate an integrated, edge-aware smart home energy management controller capable of dynamically scheduling residential flexible appliances, energy storage, and solar generation under time-varying tariff structures while maintaining occupant comfort boundaries. To realize this aim, the first technical objective establishes a modular and interoperable device interface layer using standardized edge middleware and sensing protocols, facilitating low-latency appliance status recognition and automated demand-response dispatch without reliance on proprietary single-vendor hardware [6, 7]. Prior prototype and testbed implementations demonstrate that edge and fog computing architectures can execute lightweight classification models within microsecond-scale execution windows on resource-constrained embedded processors, enabling reliable device state identification and demand-side coordination [8, 9]. The second objective establishes a multi-objective optimization architecture that simultaneously minimizes residential electricity expenditure, restricts peak-to-average load ratios, and mitigates storage battery degradation and distribution transformer stress. Prior scheduling formulations show that incorporating battery degradation costs, transformer thermal loading models, and multi-agent coordination into dispatch decisions prevents transformer overloading and curtails peak power demands across single-dwelling and clustered residential environments [10–12].

The third technical objective deploys an interpretable decision-support and forecasting module combining predictive building thermal modeling and renewable generation estimation to ensure robust control execution under real-world operational uncertainties. Because deterministic scheduling frameworks often suffer from constraint violations or suboptimal dispatch when subjected to solar intermittency and model discrepancies, incorporating stochastic optimization and dynamic setpoint adjustments offers a proven path to robust performance [13, 14]. Prior studies confirm that integrating predictive forecasting with multi-objective reinforcement learning or hierarchical model predictive control preserves indoor thermal comfort envelopes while enhancing self-consumption of local photovoltaic generation [15–17]. Furthermore, drawing on ante-hoc and post-hoc model interpretability frameworks enables transparent decision rationale for automated load shifting, addressing the trust and adoption barriers common to black-box machine learning in building management [5]. By linking multi-zone thermal dynamics with appliance flexibility, the integrated architecture balances energy cost minimization, battery life preservation, and user satisfaction [18–20].

Success will be measured against rigorous comparative baselines and functional completion criteria across a phased evaluation protocol progressing from empirical trace-driven simulations to real-time hardware-in-the-loop and laboratory testbed configurations [14]. The project defines binary validation success across four primary criteria: first, the integrated edge controller must achieve statistically significant reductions in total electricity costs and peak-to-average load ratios relative to conventional rule-based scheduling and deterministic mixed-integer baseline controllers across time-of-use and dynamic pricing profiles [12, 21]; second, the predictive thermal controller must maintain indoor temperature within defined occupant comfort envelopes with less than two percent boundary violation time across multi-day heating and cooling test horizons [13, 16]; third, the optimization framework must demonstrate active transformer peak loading and battery degradation mitigation compared to uncoordinated charging baselines [10, 11]; and fourth, the edge appliance recognition and control dispatch loop must maintain deterministic algorithmic execution within sub-second latency bounds on target embedded hardware [8]. Achieving these criteria will confirm the operational viability, efficiency, and stability of the proposed edge energy management framework.

4 Approach and Work Plan

Integrating edge-oriented hardware architectures with predictive supervisory dispatch addresses persistent operational challenges in residential energy coordination. The selected evidence demonstrates that open edge computing middleware can support multi-device interoperability and load disaggregation across smart metering networks [7], while modular communication interfaces enable secure integration with existing home automation infrastructure [6]. Furthermore, dedicated micro-controller sensing and switching enclosures have validated that device-level energy monitoring and direct load actuation produce measurable weekly energy savings across diverse residential profiles [9]. However, empirical and simulation studies indicate that conventional deterministic scheduling and unconstrained heuristic controllers struggle to maintain occupant thermal comfort or avoid energy losses when confronted with solar intermittency and model inaccuracies [13, 14]. The proposed difference combines an interoperable edge middleware platform with hierarchical-stochastic model predictive control as the designated primary method for this project. This architectural integration directly resolves the gap between physical hardware actuation and uncertainty-aware dispatch, ensuring robust operation under dynamic grid tariffs, user comfort limits, and storage degradation constraints.

Hierarchical-stochastic model predictive control serves as the single primary method for the core energy management system, governing the optimal dispatch of battery storage, rooftop photovoltaics, and flexible thermal loads. Within this formulation, deep-learning predictive models generate rolling-horizon forecasts of solar generation and building load demands [14], while the stochastic predictive controller explicitly accounts for both forecast uncertainties and physical building model inaccuracies to reduce operational costs without excessive temperature constraint violations [13]. Alternative methods identified in the literature, including deep reinforcement learning for dynamic indoor temperature setpoints [16], fuzzy metaheuristic optimization [20], and deterministic rule-based controllers [13, 14], are established as prior work and baseline comparators against which the performance of the primary hierarchical-stochastic controller is systematically evaluated.

The work plan executes in a strictly sequential pattern across four defined phases. The project commences with Phase 1: Requirements Definition and Hardware Architecture Design, which encompasses defining operational requirements, interface standards, and edge sensing topology across appliances, smart meters, and distributed generation resources using standardized protocol schemas and microservice architectures [6, 7]. Following Phase 1 completion, the project advances to Phase 2: Control Algorithm Formulation and Predictive Modeling, which executes the mathematical formulation and software development of the multi-objective hierarchical-stochastic dispatch algorithm, integrating machine learning forecasting modules and multi-zone physical constraint parameters [13, 14].

Continuing the sequential workflow, the project transitions to Phase 3: Edge Middleware Integration and Simulation Benchmarking, which couples the control algorithm codebase with edge gateway firmware and smart actuation interfaces, followed by rigorous controller-hardware-in-the-loop simulation across standardized residential demand and solar profiles [7, 14]. Finally, Phase 4: Experimental Prototype Validation and Performance Analysis deploys the complete edge-managed system into an experimental multi-device smart home testbed to empirically quantify net electricity cost savings, peak load shifting efficacy, comfort maintenance, and local execution latency [6, 9, 16].

5 Expected Outcomes and Impact

The primary technical outputs of this research encompass a modular edge-computing middleware architecture, an integrated multi-zone predictive dispatch engine, and validated open communication protocols for residential energy coordination. By translating the architectural integration established in the approach into deployable software and edge hardware configurations, the project generates fully functional supervisory interfaces capable of executing real-time appliance scheduling, storage dispatch, and multi-device load disaggregation [7]. Prior hardware prototypes have demonstrated that dedicated microcontroller and edge switching enclosures achieve measurable weekly energy savings across distinct residential consumer profiles [9], while modular and secure smart home architectures successfully integrate with existing home automation interfaces without proprietary lock-in [6]. Building on these foundational capabilities, the proposed hierarchical-stochastic control output directly resolves the performance degradation caused by solar generation uncertainties and physical building model inaccuracies, delivering lower financial expenses and fewer indoor temperature violations than uncoordinated or deterministic control schemes [13]. Real-time rolling-horizon optimization and power converter coordination further prevent operational energy losses during setpoint update intervals [14], ensuring that the delivered software models operate reliably across diverse residential load patterns.

At the end-user level, residential prosumers and household occupants represent the immediate direct beneficiaries of the system, gaining automated energy efficiency, improved renewable self-consumption, and robust protection of indoor comfort bounds. In simulated thermal-electric building configurations, model predictive control of heat pumps, photovoltaic generation, and battery storage has been shown to reduce operational costs by 11.6% while curtailing solar energy loss to 21.5% of baseline levels and preventing auxiliary heating operation [17]. Combining intelligent thermostat management with mixed-integer linear scheduling has similarly demonstrated daily cost reductions of 53.2% under dynamic tariff structures while actively accounting for battery degradation and bidirectional vehicle-to-grid power flows [19]. Dynamic setpoint algorithms driven by predictive learning maintain indoor conditions within 1% of specified comfort boundaries while shifting over 10% of flexible loads to increase renewable consumption [16], and stochastic appliance dispatch across smart plugs achieves average cost savings of 40% to 48% across real-time, time-of-use, and critical peak pricing regimes [22]. Furthermore, metaheuristic and adaptive optimization frameworks resolve multi-parameter scheduling challenges within 60 seconds of computation while substantially reducing electricity purchase expenses [20], and hybrid demand response controllers reduce grid import dependency by 79% while moderating peak battery utilization [23].

Beyond individual dwellings, the project generates systemic value for distribution grid operators, energy aggregators, and community-level decarbonization initiatives. Deploying localized optimization across aggregated residential clusters alleviates peak feeder stress, with policy gradient methods demonstrated to reduce aggregate peak loads by 26.3% and overall energy costs by 27.4% across multi-building benchmarks [24]. Furthermore, decentralized multiagent transactive frameworks enable localized peer-to-peer energy trading and demand flexibility procurement that mitigate neighborhood transformer overloading at negligible infrastructure cost, while securing 15% to 20% cost savings for participating households without exposing sensitive consumer consumption data to external aggregators [10]. By aligning local edge execution with transactive grid coordination, the project provides a scalable foundation for non-intrusive demand response, enhances the hosting capacity of existing electrical infrastructure for intermittent renewables, and accelerates the broader transition toward resilient, low-carbon residential energy systems.

6 Feasibility and Execution Readiness

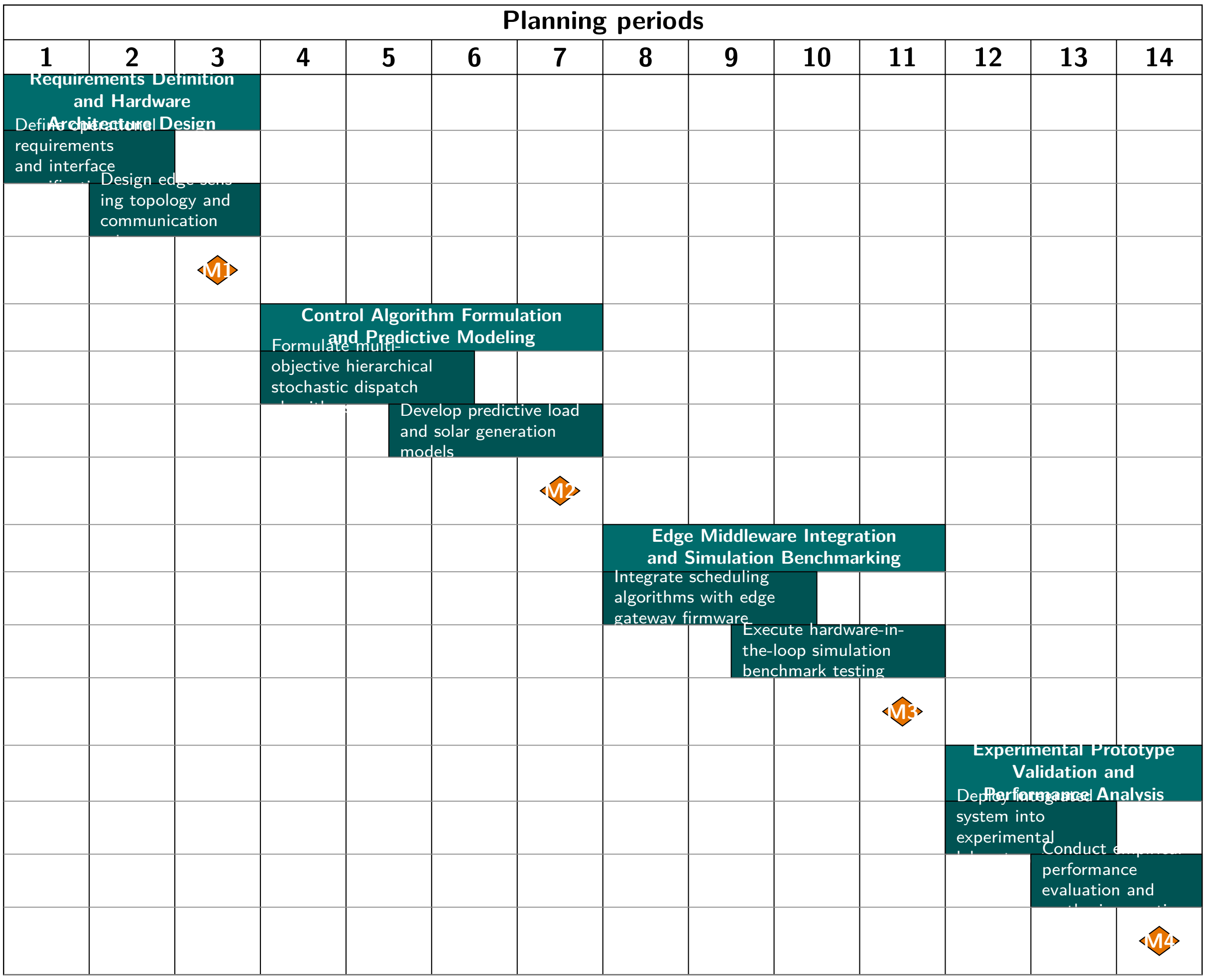
The proposed execution plan is grounded in realistic engineering bounds, leveraging mature hardware interfaces, standard computational solvers, and validated supervisory architectures. A primary operational challenge in smart home energy management is achieving reliable multi-device interoperability across disparate sensing and switching hardware without introducing prohibitive communication latencies. Precedent in the reviewed literature confirms that open edge-computing middleware utilizing microservice frameworks and standardized communication networks can reliably perform real-time load monitoring and device-level disaggregation [7]. Furthermore, modular smart home architectures deployed across dedicated residential testbeds demonstrate that standard communication interfaces and semantic web standards maintain functional security and system integrity when coupled with existing automation platforms [6]. Physical switching feasibility is further substantiated by empirical deployments of microcontroller-based relay enclosures and smart metering systems that successfully coordinate residential appliance loads and demand-response signaling [9, 25]. In industrial and multi-building facilities, layered Internet of Things middleware and customized metering networks have similarly proven stable during automated scheduling of heavy climate-control loads [26]. By building directly upon these validated hardware patterns, the project confines physical integration risk to well-characterized interface boundaries.

Algorithmic feasibility is supported by established formulations in building climate control, machine learning forecasting, and residential storage optimization. Advanced building control frameworks document standard co-simulation workflows, numerical solvers, and supervisory architectures capable of mitigating environmental and structural disturbances [27]. Specifically, simulation studies demonstrate that hierarchical-stochastic model predictive control effectively suppresses indoor temperature constraint violations while reducing operational expenses under joint forecast uncertainty and building parameter inaccuracies [13]. The required forecasting accuracy is achievable through proven regression and deep learning architectures, such as gradient boosting regression trees and long short-term memory networks, which have demonstrated high predictive fidelity for building energy consumption and solar irradiance profiles [14, 28, 29]. Residential battery degradation and state-of-charge management are likewise anchored in structured multi-objective optimization and mixed-integer linear programming formulations documented for distributed energy resources and electric vehicle integration [30, 31]. Progressing through controller-hardware-in-the-loop testing and experimental prototype deployment as outlined in the evaluation strategy ensures that the committed performance and savings targets are systematically validated against established baseline methods.

Execution readiness is reinforced by clear risk-mitigation strategies and credible fallback mechanisms designed to handle computational constraints and sensor anomalies. The primary execution risk involves potential optimization latency during edge-gateway execution under complex stochastic horizons or noisy sensor feeds [28, 32]. To address this constraint, the architecture incorporates layered execution logic where supervisory setpoints are updated at fixed intervals while a real-time rule-based controller operates at a finer time resolution at the power electronics converter level to prevent operational losses during calculation intervals [14]. If edge computational resources become constrained, the optimization horizon can seamlessly fall back to deterministic mixed-integer linear programming [31] or heuristic load-shedding algorithms that schedule flexible devices according to preset consumer priority rules [33, 34]. Should environmental sensor streams or local communication links experience dropouts, the system will temporarily revert to robust rule-based baseline schedules or adaptive fuzzy logic controllers [20, 34], ensuring fail-safe continuity of essential domestic heating and power services without compromising occupant safety or comfort.

7 Timeline and Milestones

The project executes in a strictly sequential progression across four phases, moving from foundational architecture definition to empirical testbed validation. Intermediate milestones serve as critical quality gates to verify interface compatibility, algorithmic convergence, and firmware readiness prior to full hardware integration. This staged structure ensures comprehensive risk mitigation and rigorous verification against target operational metrics at each development horizon.



Legend.

- **M1** (Milestone; Planning periods 3): Architectural specification report completed
- **M2** (Milestone; Planning periods 7): Forecasting and optimization codebase validated
- **M3** (Milestone; Planning periods 11): Simulation benchmark evaluation completed
- **M4** (Milestone; Planning periods 14): Final testbed validation report delivered

Figure 1: Project timeline using relative planning periods across 4 phases

8 Budget and Justification

The proposed budget reflects the core personnel and experimental infrastructure required to design, integrate, and validate the edge-aware smart home energy management system across the fourteen planning periods. Primary cost drivers include specialized engineering personnel for control formulation, firmware integration, and experimental validation, alongside hardware-in-the-loop simulation equipment and physical sensing components needed for multi-device testing. Expenditure is distributed sequentially across the four work packages to align resource availability directly with architectural specification, algorithmic development, hardware integration, and testbed evaluation milestones.

Table 1: Summary budget by category, active periods, and total.

Category	**Active periods**	**Total**
Personnel	P1; P4; P6; P8; P12	74,000
Equipment	P9	12,000
Materials and Supplies	P2; P10; P12	11,000
Computing	P5	4,000
Dissemination	P14	2,500
Grand Total	P1-2; P4-6; P8-10; P12; P14	103,500

P = relative planning period.

Table 2: Itemized budget line items.

Budget item	**Details**
Systems Architect and Protocols Lead Personnel P1; Amount: 14,000	**Work package:** Architecture Specification and Device Protocol Interoperability *Justification:* Effort allocation for defining system operational requirements, interface standards, and device communication schemas.
Edge Interface Sensing and Microcontroller Prototyping Modules Materials and Supplies P2; Amount: 3,500	**Work package:** Architecture Specification and Device Protocol Interoperability *Justification:* Component procurement for prototype edge sensing nodes and standard interface evaluation kits.
Lead Optimization and Control Research Engineer Personnel P4; Amount: 16,000	**Work package:** Multi-Objective Scheduling and Stochastic Forecasting Development *Justification:* Effort allocation for mathematical formulation of the multi-objective hierarchical-stochastic dispatch algorithm.
Predictive Modeling and Training Compute Resources Computing P5; Amount: 4,000	**Work package:** Multi-Objective Scheduling and Stochastic Forecasting Development *Justification:* Cloud compute allocation for training deep-learning solar generation and dynamic building load forecasting models.
Machine Learning Research Specialist Personnel P6; Amount: 14,000	**Work package:** Multi-Objective Scheduling and Stochastic Forecasting Development *Justification:* Effort allocation for developing and tuning predictive load and solar generation regression models.

Budget item	Details
Embedded Firmware and Middleware Engineer Personnel P8; Amount: 15,000	**Work package:** Edge Middleware Assembly and Hardware-in-the-Loop Simulation *Justification:* Effort allocation for integrating scheduling algorithms into edge gateway firmware and microservices.
Hardware-in-the-Loop Interface and Simulation Bench Equipment P9; Amount: 12,000	**Work package:** Edge Middleware Assembly and Hardware-in-the-Loop Simulation *Justification:* Interface hardware and real-time emulation bench for closed-loop validation across standard residential profiles.
Smart Plugs, Relays, and Metering Subassembly Units Materials and Supplies P10; Amount: 4,500	**Work package:** Edge Middleware Assembly and Hardware-in-the-Loop Simulation *Justification:* Dedicated switching enclosures and automated metering components for controller integration.
Experimental Validation and Testbed Specialist Personnel P12; Amount: 15,000	**Work package:** Physical Testbed Evaluation and Impact Assessment *Justification:* Effort allocation for physical testbed deployment, empirical data logging, and performance benchmark analysis.
Laboratory Testbed Consumables and Sensor Instrumentation Materials and Supplies P12; Amount: 3,000	**Work package:** Physical Testbed Evaluation and Impact Assessment *Justification:* Environmental monitoring sensors and wiring supplies for multi-device testbed integration.
Technical Documentation and Synthesis Dissemination Dissemination P14; Amount: 2,500	**Work package:** Physical Testbed Evaluation and Impact Assessment *Justification:* Costs for compiling final technical synthesis reports and project documentation.

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