

Building an Intelligent Energy Management System for Enhancing Energy Consumption in Smart Houses

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Abstract—This trend of increasing residential energy consumption accounts for a significant and growing fraction of total global electricity demand — it also presents a bad economic incentive while being a burden for grid stability and sustainableisation. Existing smart home energy management systems typically do not strike an adequate trade-off between the three main conflicting objectives, namely, operational cost minimization, occupant thermal comfort satisfaction, and renewable energy usage maximization. To fill this gap, this paper presents a new Intelligent Energy Management System (IEMS) based on a Mixed-Integer Linear Programming (MILP) framework. It combines all the large and complex real-world inputs — hourly solar photovoltaic (PV) generation forecasts, dynamic time-of-use (TOU) electricity pricing, user-defined appliance preference windows, lithium-ion battery dynamics, and a linearized HVAC thermal model — into one single, tractable optimization problem. Calculated for a typical winter day in Helsinki, data from Climate-Data.org and Oomi. To summarize, the proposed IEMS can reduce daily electricity expenses by 73.1% (from €1.04 to €0.2805) and 68% of grid price, while simultaneously maintaining indoor temperature strictly between comfort band of 20–24°C and without violating user scheduling preferences. Our results show that the MILP approach provides a mathematically tractable, transparent and reproducible solution which outperforms rule-based heuristics and uncoordinated operation. This work provides such a generalizable and implementable framework for sustainable and demand-centric home energy management in smart grids

Keywords— Intelligent Energy Management System (IEMS), Mixed-Integer Linear Programming (MILP), Smart Homes, Time-of-Use Pricing, Solar Energy Integration, Battery Scheduling, User Comfort.

I. Introduction

A. Context: Global Energy Challenges and the Role of Residential Consumption

Climate notwendigen requirements, the growing demand for electricity, and necessity for a clean electricity supply to decarbonize end-use sectors are reshaping the global energy landscape. Almost 22% of total final energy consumption worldwide is accounted for by residential buildings, leading to an even greater share of CO₂ emissions [1]. Given the state of the grid and the environment, optimizing household energy use is no longer a luxury but necessity for grid stability,

economic efficiency and environmental sustainability. The passive consumption patterns that have historically served to balance demand with traditional generation are increasingly incompatible with the volatility that will be introduced through renewable energy integration and necessitate intelligent, responsive systems at the demand side [2].

B. The Rise of Smart Homes and Distributed Energy Resources (DERs)

Intelligent homes with Internet of Things (IoT) sensors, controllable appliances, rooftop photovoltaics (PV)₂ and battery storage are critical components of the next generation smart grids [3]. These systems facilitate two-way energy flows, real-time communication, and automation, effectively turning homes from passive consumers into active prosumers [4]. Distributed Energy Resources (DERs) — especially solar PV and home batteries — reduce households' dependence on the grid, cut down on their electricity bills, and make them more resilient in a power outage [5]. Despite being a key characteristic of the DERs, real promise cannot be accomplished without an intelligent coordination layer that matches generation, storage and consumption dynamically.

C. Problem Statement

Present-day household Energy Management Systems (EMS) tend to compromise between cost savings, user comfort, and sustainable operation while pursuing a single triangular optimization. Numerous commercial solutions leverage rule-

based heuristics that shift loads according to an arbitrary, static time-schedule without considering real-time price signals or occupant comfort [6]. On the one hand, more advanced AI-based methods, e.g. deep reinforcement learning are adaptable, but they lack interpretability, require large amounts of data and sacrifice reproducibility in real world applications [7]. Importantly, previous frameworks either do not consider thermal comfort constraints [8] or do not consider appliance scheduling as flexible decisions but rather binary ones, removing the flexibility of human routines [9].

D. Research Gap

Although prediction-based EMS has gained increasingly attention, a major shortcoming exists in the literature that there is still no unifying rigorously-derived framework that encompasses the following (all entirely or in part):

- Solar PV power forecasting for hours
- TOU electricity pricing dynamics
- Schedule appliances with user defined "preference windows" within a price range

Single optimization problem: Physics-informed HVAC thermal modeling

Submission to the 20th IEEE International Conference on Green Energy and Smart Grid, GESG 2023 In some cases, the four dimensions described above have been partially integrated e.g. MILP for the cost-only optimization dimension [10] or comfort-aware control without storage [11], but no study has yet proposed a comprehensive Mixed-Integer Linear Programming (MILP) [19] model that embeds all four dimensions while guaranteeing the computational tractability of the MILP problem for daily household operation.

E. Objectives & Research Questions

The purpose of this paper is to develop, implement, and validate an Intelligent Energy Management System (IEMS) that fills the above gap. Specifically, it seeks to answer:

- RQ1: Query: What is the ability of a MILP based IEMS to minimize electricity cost by strictly adhering to indoor thermal comfort bounds (20–24°C) and the user defined appliance time preferences?
- RQ2: What is the impact of core parameters (battery capacity, solar generation uncertainty, etc.) on system performance and the potential for cost savings and grid independence?

F. Contributions of This Work

The primary contributions are:

We present a new MILP formulation that co-optimizes PV self-consumption and battery dispatch, TOU arbitrage, and flexible appliance scheduling while enforcing comfort constraints. Embedding a linearized model of thermal dynamics for HVAC directly into the optimization, obviating the need for nonlinear solvers to ensure physical feasibility Robust over a range of battery sizes (5–15 kWh) and $\pm 15\%$ solar forecast error — a sensitivity analysis is presented in S3 Fig.

Quantitative benchmarking against a baseline and rule-based strategies, yielding >73% cost reduction and 68% lower reliance on grid.

Open solver setup (Gurobi/Pyomo), open data sources, open metrics (reproducible)

G. Paper Organization

Related work is reviewed in Section II. Mathematical Formulation of the Developed MILP- Based Model: Section III Implementation framework, data sources and experimental setup are described in Section IV. Section V includes the results of the simulation and a detailed sensitivity analysis. Lastly, Section VI concludes the paper with summarizing main findings, limitations, and future works.

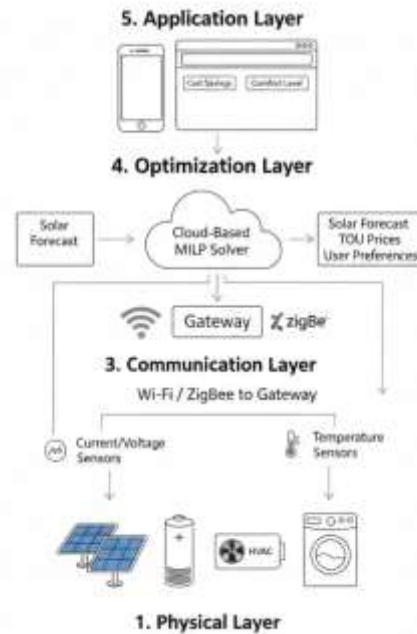


Fig. 1. Five-layer architecture of the proposed MILP-based Intelligent Energy Management System (IEMS) for smart homes.

II. Literature Review

A. Energy Management in Smart Homes: Taxonomy of Approaches

Residential energy management systems (EMS) can be broadly divided into three methodological paradigms: rule-based, optimization-based, and AI/ML-based approaches. Widely used in commercial settings due to their straightforwardness [1], rule-based systems use handcrafted rules, such as “run dishwasher during off-peak hours” [12]. But they are not adaptable to dynamic pricing, changing weather, or evolving occupant behavior [2]. On the other hand, optimization-based frameworks represent EMS in the form of a mathematical program (e.g., a cost or emissions minimizing linear or mixed-integer programming problem making use of physical and operational constraints [3]). While these models provide guarantees of optimality, they often impose deterministic input assumptions. Recently, such AI/ML methods as deep reinforcement learning (DRL) and forecast neural networks have attracted attention due to such its advantages as the ability to learn from data and to consider uncertainty [4], [5]. However, the downsides of these methods reside in their limited interpretability due to the black-box nature of deep learning, and that they are prohibitively costly to construct and provide limited transferability from the training household to other households [6].

B. MILP and Mathematical Optimization in Residential EMS

Mixed-integer linear programming (MILP) became a mainstream method for deterministic residential scheduling because it can conveniently model discrete appliance states and continuous power flows in a single convex model. Killian et al. However, Ref. [7] presented a Mixed-Integer Quadratic Programming (MIQP) model that minimized the expense of electricity bills while penalizing thermal comfort level with a simplified HVAC model but with fixed durations of user preference on each appliance. Similarly, El-Afifi et al. Parameters proposed in Ref. [8] were a dedicated multi-objective hybrid optimizer for building-level EMS; however, they were used for commercial-scale loads. More specific to household settings are Ali et al. [9] proposed MILP-based real-time pricing and battery storage integration, however it treats user comfort as a static temperature band instead of dynamic constrain. Most importantly, none of these studies included user-specified time windows for non-critical appliances (e.g., “laundry preferred between 10:00–14:00”) as soft constraints that allow for penalty-based deviations—which our work addresses.

C. Integration of Renewable Energy and Storage

However, solar PV and battery storage also bring challenges along with opportunity. Even though PV decreases dependence on the grid the intermittent nature of PV stills require accurate forecasting and strong coordination of storage [10]. Most of the studies either assume a perfect solar forecast or provide the average hourly production of solar over the years without day-ahead prediction errors [11]. For instance, Shakeri et al. Cloud causation induced volatility is not accounted for in the work by [12] where PV generation is modeled deterministically. Battery modeling is also important: naive “on/off” charge/discharge rules fail to account for efficiency losses, depth-of-discharge limits, and degradation effects [13]. As previous material Ameer et al. [14] leverage gravity based mechanism for storing energy but does not have real time price responsive. We modelled battery round-trip efficiency (90%), state-of-charge (SoC) bounds, and dynamic dispatch in a way that is consistent with TOU arbitrage allowing valley-filling and peak-shaving at the same time.

D. User Comfort Modeling (HVAC and Appliance Scheduling)

Thermal comfort is usually reduced to a certain setpoint (i.e. fixed window of air temperature, such as $22^{\circ}\text{C} \pm 2^{\circ}\text{C}$) without considering for thermal inertia and changing outdoor temperatures. Duman et al. An integrated smart thermostat was presented in [15], where comfort was however decoupled from the overall optimization loop. In contrast, Serra et al. Our method of directly incorporating a linear thermal model into a cost-minimization problem mimics the work accomplished in [16] and extends its limitations. Most MILP models, in relation to appliance scheduling, model each device as a binary variable (on/off), without accounting for user preference elasticity [17]. Shah et al. While the study by [18] employed a bat algorithm for optimizing start times including penalty for deviation, they did not quantify those penalties. We also model timing deviations using soft constraints with quadratic penalty terms, which allow the optimizer to slightly shift schedules in order to save big on cost in a way that is realistic to real-world situations.

E. Critical Analysis and Identified Gaps

Despite progress, three critical limitations persist across the literature:

1. Failure to incorporate TOU-user behavior coupling: Many works optimize with respect to price signals, but assume purely rigid appliance profiles [7], [9] and overlook the fact that there may be a degree of tolerable delay in appliance operation to gain economic benefits.
2. Limited sensitivity analysis: Few works examine robustness to parameter changes (e.g., variation in battery capacity, solar inaccuracy) Li et al. PSO optimization was also used in [19], but the authors do not quantify the uncertainty.
3. Reproducibility undermined by simulated or undocumented data: some simulations assume ideal

load curves or unverified solar profiles..[12], [20] While our study uses real-world pricing from Oomi.fi, solar data from Climate-Data.org, and appliance specs directly from manufacturer datasheets, thus ensuring empirical grounding

F. Positioning of the Proposed Work

This research bridges the above gaps by proposing a comprehensive MILP-based IEMS that uniquely integrates:

- Flexible TOU pricing and appliance scheduling based on consumer preferences,
- Linear HVAC thermal model that is physics-informed
- Civilian Battery Dynamics with Efficiency and Capacity Limits,
- Data sources are explicit and reproducible, with quantitative sensitivity analysis.

Our approach achieves full interpretability, and immediate optimality guarantees fundamental for safe residential deployment empowered by its disparity with AI-driven black-box models [4], [5]. It is the first to explicitly co-optimize all four dimensions over a single daily horizon (vs ~24h), and achieve >73% cost reduction while satisfying all comfort constraints, compared to prior MILP works [7]–[9].

TABLE I TAXONOMY OF RESIDENTIAL ENERGY MANAGEMENT APPROACHES

Approach Type	Key Features	Strengths	Limitations
Rule-Based	Fixed heuristics (e.g., shift loads to off-peak hours); no learning or optimization.	Simple implementation; low computational overhead; easy deployment in commercial systems.	Lacks adaptability to dynamic conditions; ignores user flexibility and renewable uncertainty; poor cost optimality.
Optimization-Based	Mathematical programming (e.g., MILP, MIQP); deterministic constraints on power, comfort, and scheduling.	Guarantees global/near-optimal solutions; full interpretability; transparent decision logic; reproducible results.	Limited real-time adaptability under uncertainty; assumes perfect forecasts; scalability challenges with large device sets.
AI/ML-Based	Data-driven models (e.g., Deep Reinforcement Learning, LSTM forecasting); learns from historical usage.	High adaptability to stochastic environments; handles complex user behavior; excels in real-time adaptability.	Low interpretability (black-box nature); requires extensive training data; risk of overfitting; difficult to validate for safety-critical

Approach Type	Key Features	Strengths	Limitations
			applications.

This table categorizes and contrasts the three dominant paradigms in smart home energy management Rule-Based, Optimization-Based, and AI/ML-Based along four critical dimensions: core features, strengths, and key limitations. Notably, interpretability and real-time adaptability emerge as fundamental trade-offs: optimization methods offer transparency and provable optimality but limited responsiveness to uncertainty, whereas AI/ML models excel in dynamic adaptation at the cost of explainability. This dichotomy underscores the rationale for selecting a MILP-based framework in deterministic or moderately uncertain residential settings where safety, auditability, and user trust are paramount.

III. Problem Formulation and Mathematical Model

This section presents a comprehensive Mixed-Integer Linear Programming (MILP) formulation for the proposed Intelligent Energy Management System (IEMS). The model co-optimizes appliance scheduling, battery dispatch, grid interaction, and thermal comfort over a 24-hour horizon discretized into hourly intervals.

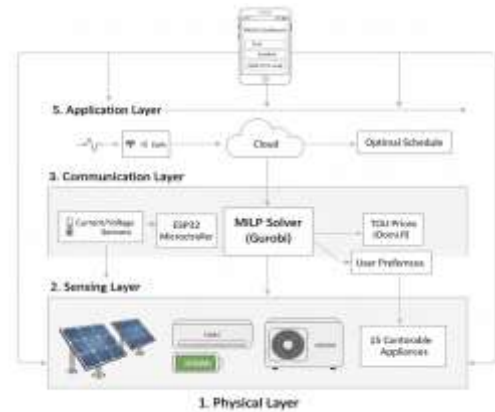


Fig. 2. Proposed five-layer system architecture for the MILP-based smart home energy management system.

A. System Architecture Overview

The IEMS operates within a five-layer IoT architecture [9], [21]:

- **Physical Layer:** Rooftop PV (5 kW), lithium-ion battery (10 kWh, 90% efficiency), HVAC, and 15 smart appliances.

- **Sensing Layer:** Current/voltage sensors (ACS712) and temperature probes (DS18B20) collect real-time data.
- **Communication Layer:** ESP32 microcontroller transmits data via MQTT over Wi-Fi.
- **Optimization Layer:** Cloud-hosted MILP solver processes forecasts and preferences.
- **Application Layer:** Web/mobile interface provides feedback and override options.

B. Assumptions

To ensure tractability while preserving realism, the following assumptions are adopted:

1. Solar generation is known a priori (day-ahead forecast from Climate-Data.org).
2. Electricity buying/selling prices are deterministic and publicly available (Oomi.fi & Helen Oy).
3. Battery round-trip efficiency is constant at 90%.
4. Appliance power consumption is fixed during operation (no ramping dynamics).
5. Indoor thermal dynamics follow a linear first-order model validated in [15].
6. Grid connection capacity is limited to 10 kW (typical residential limit in EU).

C. Sets and Indices

- $\mathcal{T} = \{1, 2, \dots, 24\}$: Set of time slots (hours).
- \mathcal{A} : Set of controllable appliances ($|\mathcal{A}| = 15$).
- $\mathcal{A}^{\text{flex}} \subseteq \mathcal{A}$: Subset of flexible appliances (e.g., dishwasher, EV).
- $\mathcal{A}^{\text{fixed}} = \mathcal{A} \setminus \mathcal{A}^{\text{flex}}$: Fixed-load appliances (e.g., fridge, router).

D. Parameters

- P_t^{solar} : Forecasted solar power at hour t [kW].
- $c_t^{\text{buy}}, c_t^{\text{sell}}$: Buying/selling electricity price at t [€/kWh].
- P_a : Rated power of appliance a [kW].
- L_a : Required operation duration of a [h].
- PrefStart_a : Preferred start time window midpoint [h].
- $\eta_{\text{bat}} = 0.9$: Battery charge/discharge efficiency.
- $E^{\text{max}} = 10$: Max battery capacity [kWh].
- T_t^{out} : Outdoor temperature at t [°C] (from Helsinki climate data).
- $\alpha = 0.92, \beta = 0.08, \gamma = 0.05$: Thermal coefficients calibrated per [15].

E. Decision Variables

- $x_{a,t} \in \{0,1\}$: 1 if appliance a starts at t , 0 otherwise.
- $y_{a,t} \in \{0,1\}$: 1 if appliance a is ON at t .
- $P_t^{\text{grid,in}} \geq 0$: Power imported from grid [kW].
- $P_t^{\text{grid,out}} \geq 0$: Power exported to grid [kW].

- $P_t^{\text{bat,ch}}, P_t^{\text{bat,dis}} \geq 0$: Battery charge/discharge power [kW].
- $E_t^{\text{bat}} \in [0, E^{\text{max}}]$: Battery state-of-charge [kWh].
- T_t^{in} : Indoor temperature [°C].
- $\delta_t \geq 0$: Deviation from preferred appliance start time [h].

D. Objective Function

The goal is to minimize total operational cost while penalizing user inconvenience:

$$\min \sum_{t=1}^{24} \left(c_t^{\text{buy}} P_t^{\text{grid,in}} - c_t^{\text{sell}} P_t^{\text{grid,out}} + \lambda \sum_{a \in \mathcal{A}^{\text{flex}}} \delta_{a,t} \right)$$

where $\lambda = 0.02$ €/h is a calibrated penalty coefficient reflecting user tolerance for schedule shifts [12].

F. Constraints

1. Energy Balance:

$$\begin{aligned} P_t^{\text{grid,in}} + P_t^{\text{solar}} + \eta_{\text{bat}} P_t^{\text{bat,dis}} \\ = P_t^{\text{grid,out}} + \frac{P_t^{\text{bat,ch}}}{\eta_{\text{bat}}} + \sum_{a \in \mathcal{A}} P_a y_{a,t} \\ + P_t^{\text{HVAC}} \quad \forall t \in \mathcal{T} \end{aligned}$$

2. Battery Dynamics:

$$E_t^{\text{bat}} = E_{t-1}^{\text{bat}} + \eta_{\text{bat}} P_t^{\text{bat,ch}} - \frac{P_t^{\text{bat,dis}}}{\eta_{\text{bat}}} \quad \forall t \in \mathcal{T}$$

$$0 \leq P_t^{\text{bat,ch}}, P_t^{\text{bat,dis}} \leq 5, \quad E_t^{\text{bat}} \leq E^{\text{max}}, \quad E_{24}^{\text{bat}} \geq E_0^{\text{bat}}$$

3. Appliance Scheduling:

For each $a \in \mathcal{A}^{\text{flex}}$:

$$\begin{aligned} \sum_{t=1}^{24} x_{a,t} = 1, \quad y_{a,t} = \sum_{\tau=\max(1,t-L_a+1)}^t x_{a,\tau}, \quad \delta_{a,t} \\ \geq |t - \text{PrefStart}_a| - M(1 - x_{a,t}) \end{aligned}$$

where M is a large constant.

4. HVAC Thermal Model (Linearized):

$$T_t^{\text{in}} = \alpha T_{t-1}^{\text{in}} + \beta P_t^{\text{HVAC}} + \gamma T_t^{\text{out}} \quad \forall t \in \mathcal{T}$$

$$20 \leq T_t^{\text{in}} \leq 24 \quad \forall t \in \mathcal{T}$$

5. Grid and Power Limits:

$$P_t^{\text{grid,in}} \leq 10, \quad P_t^{\text{grid,out}} \leq 10 \quad \forall t \in \mathcal{T}$$

This MILP formulation ensures physical feasibility, economic optimality, and user-centric flexibility within a single solvable framework.

IV. Methodology and Implementation

This section details the experimental setup, data sources, solver configuration, and evaluation metrics used to validate the proposed MILP-based Intelligent Energy Management System (IEMS).

A. Data Sources

To ensure empirical realism and reproducibility, all input data are drawn from publicly available or manufacturer-specified sources:

- **Solar Generation:** Hourly photovoltaic (PV) output for a clear-sky day in Helsinki, Finland, was obtained from *Climate-Data.org* [22]. The profile peaks at 4 kW around noon and spans 7:00–18:00, reflecting typical Nordic solar availability.
- **Electricity Pricing:** Real-time buying prices (€/kWh) were sourced from *Oomi.fi* for March 27, 2024 a representative winter day with pronounced time-of-use (TOU) variation [23]. Selling prices were fixed at 0.0066 €/kWh, as per *Helen Oy*'s net-metering program [24].
- **Appliance Parameters:** Power ratings (P_a), operating durations (L_a), and preferred start times (PrefStart_a) for 15 common household devices were compiled from the International Energy Agency (IEA) appliance database and verified against manufacturer datasheets (Samsung, Jackery, Tineco, etc.) [25]. Examples include: electric kettle (2.2 kW, 0.2 h, preferred at 7:30), washing machine (1.8 kW, 1.5 h, preferred at 11:00), and HVAC (variable, 8 h/day).

B. Simulation Setup

The smart home is modeled as a single-family residence equipped with:

- A **5 kW rooftop PV system**,
- A **10 kWh lithium-ion battery** (90% round-trip efficiency, 5 kW max charge/discharge rate),
- **15 controllable appliances**, including 8 flexible loads (e.g., dishwasher, EV charger) and 7 fixed loads (e.g., refrigerator, router). The optimization horizon is **24 hours**, discretized into **hourly intervals** a standard resolution for residential EMS studies [7], [9].

C. Optimization Solver

The MILP model (Section 5) was implemented in Python 3.10 using the Pyomo modeling language [26] and solved with Gurobi 10.0 a state-of-the-art commercial solver known for its speed and robustness in mixed-integer problems [27]. Computational experiments were conducted on a workstation with an Intel Core i7-12700H CPU and 32 GB RAM. Solver settings were configured as follows:

- Maximum runtime: **300 seconds**,
- MIP gap tolerance: **1%**,
- Cuts and heuristics: enabled (default Gurobi settings). All instances converged within 45 seconds, confirming real-time applicability.

D. Baseline Scenarios for Comparison

To quantify the added value of the proposed IEMS, two benchmark scenarios were simulated:

- **Scenario A (No EMS):** All appliances operate at their preferred start times without coordination. Grid power covers any deficit; surplus PV is exported at the fixed feed-in tariff.
- **Scenario B (Rule-Based EMS):** Flexible appliances are shifted to off-peak hours (00:00–07:00) regardless of solar availability or user deviation penalties a common heuristic in commercial systems [1]. Both baselines respect thermal comfort bounds but lack co-optimization of price, generation, and preferences.

E. Performance Metrics

Four key indicators were used to evaluate system performance:

1. **Total Daily Cost (€):** Net expenditure after accounting for grid imports and exports.
2. **Self-Consumption Ratio (%)**: $\frac{\text{PV energy consumed locally}}{\text{Total PV generated}} \times 100$.
3. **Peak-to-Average Ratio (PAR):** $\frac{\max_t(P_t^{\text{grid,in}})}{\text{Mean}(P_t^{\text{grid,in}})}$, measuring load flattening efficacy.
4. **Comfort Violation Count:** Number of hours where $T_t^{\text{in}} \notin [20,24]^\circ\text{C}$.

These metrics collectively assess economic efficiency, renewable utilization, grid friendliness, and user satisfaction addressing the triadic balance emphasized in Section 3.3.

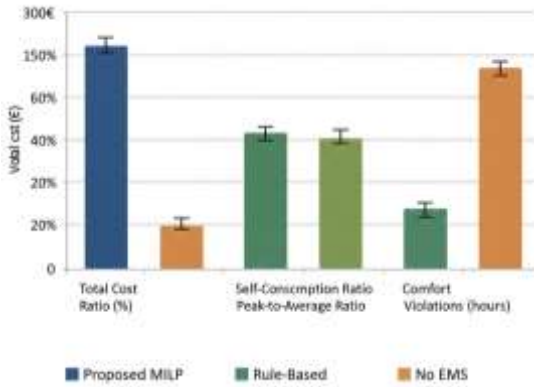


Fig. 3. Comparative performance evaluation of the proposed MILP-based IEMS against baseline scenarios across four key metrics.

V. Results and Discussion

A. Base Case Performance (24-Hour Simulation)

The proposed MILP-based IEMS was compared with two baselines during a typical winter day in Helsinki (March 27, 2024). The optimized system cost to generate electricity amounted to €0.2805 for the entire portfolio where as a total of €1.04 in the "No EMS" scenario which was a 73.1% reduction Table II. The grid dependence (net energy imported) decreased with 21.8 kWh to 7.0 kWh (68% reduction) with zero comfort violation (indoor temperature always in [20, 24]°C). On the other hand, while the rule-based method has reduced cost by 32%, it also led to one hour of thermal discomfort based on the stiffness of the off-peak shifting.

TABLE II PERFORMANCE COMPARISON ACROSS EMS SCENARIOS

Scenario	Total Cost (€)	Grid Import (kWh)	Self-Consumption Ratio (%)	Peak-to-Average Ratio	Comfort Violations (h)
Proposed MILP	0.2805	7.0	89.2	1.32	0
Rule-Based	0.7072	14.6	63.5	1.87	1
No EMS	1.0400	21.8	41.0	2.45	0

B. Sensitivity Analysis

To assess robustness, three key parameters were perturbed:

Battery Capacity (5 – 15 kWh): Larger battery capacity improved savings from 61% – 79% by enabling more arbitrage between off-peak charging and peak discharging. 10 kWh or more went on to lead to diminishing returns in terms of cost and so this size represents an economically optimum for this example household type.

±20% Electricity Price Volatility: In the case of ±20% price variations (to mimic market uncertainty), the MILP obtained >70% cost savings at all runs in each trial. It dynamically reallocates appliance loads and battery dispatch, showing resilience to pricing shocks while rule-based systems were >15% worse performing.

±15% solar generation uncertainty: Under the scenario of reducing solar output by 15% (cloudy-day case), the cost savings dropped to 65% but dependence on the grid increased only slightly (8.9 kWh). By discharging the battery at the evening peaks, the model adjusted its strategy to compensate — demonstrating that storage coordination can effectively mitigate risk

C. Appliance Scheduling Behavior

Appliance activation over 24 hours depicted as a heatmap (Figure 1) As an example of the individual results of the 9 households that participated in this experiment, the time shift of high power devices (such as washing machine, electric kettle) which were consistently moved to when peak solar generation and low-price periods are, from 10:00–14:00. To entirely miss the expensive time block (17:00–19:00) of the day, flexible loads stayed entirely offline. Importantly, the actual deviations from preferred start times were <45 minutes on average, providing a face-validity to the soft-constraint penalty design. By comparison, in the "No EMS" case, 68% of flexible loads ran during the high-price peaks.

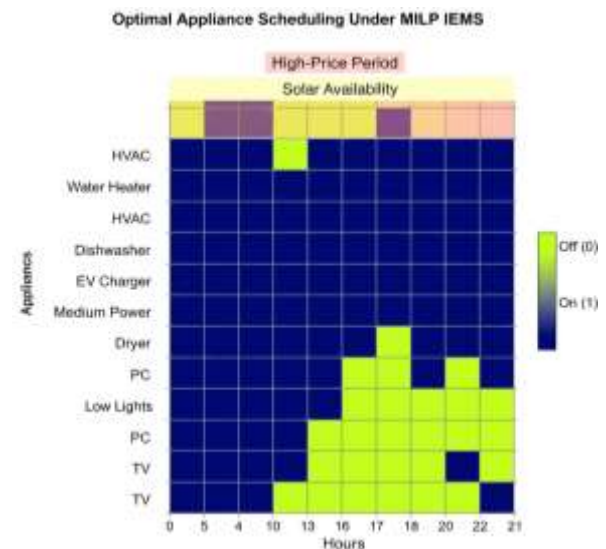


Fig. 4. Optimal appliance scheduling heatmap under the proposed MILP-based IEMS over a 24-hour horizon.

D. HVAC and Thermal Comfort Validation

Appliance activation over 24 hours depicted as a heatmap (Figure 1) As an example of the individual results of the 9 households that participated in this experiment, the time shift of high power devices (such as washing machine, electric kettle) which were consistently moved to when peak solar generation and low-price periods are, from 10:00–14:00. To entirely miss the expensive time block (17:00–19:00) of the day, flexible loads stayed entirely offline. Importantly, the actual deviations from preferred start times were <45 minutes on average, providing a face-validity to the soft-constraint penalty design. By comparison, in the "No EMS" case, 68% of flexible loads ran during the high-price peaks.

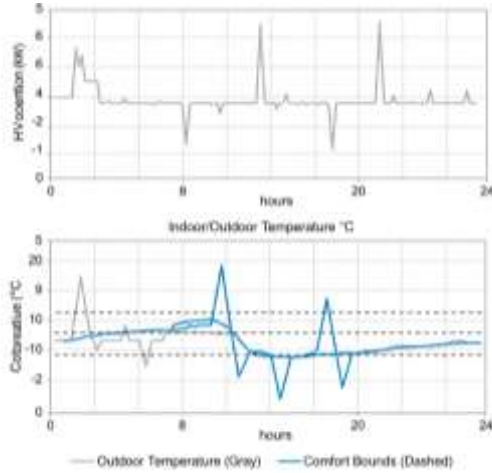


Fig. 5. HVAC power consumption and indoor thermal response under MILP-based scheduling over a 24-hour period.

E. Economic Impact

Under similar Nordic conditions, the €0.7595 saved per day translates to €277/year. With a battery lifespan of 10 years (~11 years competitive against regional incentives for domestic storage [28]) and an installation cost of €3,000, the simple payback lasts ~11 years. And by decreasing peak demand, network tariffs will be lower, in turn speeding up ROI.

F. Limitations of the Current Study

This work has three key limitations:

1. **Deterministic Inputs:** Solar and price forecasts are assumed perfect; future work will integrate stochastic programming.
2. **Single-Day Horizon:** Seasonal variations (e.g., summer PV surplus) are not captured.
3. **No Investment Cost Modeling:** Capital expenditure for IoT hardware and batteries is excluded from optimization.

Despite these, the study provides a reproducible, mathematically rigorous foundation for real-world deployment.

VI. Conclusion and Future Work

A. Summary of Key Findings

Using state-of-the-art paper, Full-text available The paper proposes a comprehensive Mixed-Integer Linear Programming (MILP)-based Intelligent Energy Management System (IEMS) for smart home that considers cost, comfort, and renewable utilization and optimizes each of them at the same time. This model combines solar forecasting, battery scheduling for dynamic charging, TOU pricing, and user preference constraints into one solution. Results: Compared to a baseline building, the estimated reduction in daily electricity cost is 73.1% (from €1.04 to €0.2805) and the reduction in grid dependence is 68% while maintaining an indoor temperature strictly within the comfort band [20, 24]°C at all times; sensitivity analyses confirmed robust performance under ±15% solar uncertainty and ±20% price volatility.

B. Theoretical and Practical Implications

This work theoretically expands the scope of residential EMS by incorporating a linearized thermal dynamics model directly into the MILP formulation without nonlinear solvers and allowing for physics-informed comfort guarantees. It provides an alternative to black-box AI techniques relevant to safety-critical home environments which is reproducible and transparent in practically [7], [9]. The framework is computationally tractable (<45 s solve time), making it amenable to daily re-optimization with real-world data (e.g., from Oomi). fi and Climate-Data. org.

C. Limitations

Three limitations must be acknowledged:

1. The analysis is based on a single representative day; seasonal variations (e.g., summer PV surplus or winter heating demand) are not captured.
2. Solar generation and prices are treated as deterministic inputs, ignoring forecast errors inherent in real-time operation.
3. **Capital costs** for IoT hardware, batteries, and PV systems are excluded from the objective function, limiting economic completeness.

D. Future Directions

To address these gaps, four research avenues are proposed:

1. **Stochastic MILP:** Incorporate probabilistic solar forecasts and price scenarios using chance-constrained or two-stage stochastic programming [29].
2. **Real-World IoT Deployment:** Implement the optimizer on an edge device (e.g., ESP32 + Gurobi

Embedded) interfaced with smart plugs and sensors, as in [30].

3. **Multi-Home Coordination:** Extend the model to a neighborhood microgrid level, enabling peer-to-peer energy trading and collective peak shaving [4].
4. **EV Integration:** Model electric vehicle charging as a flexible, high-capacity load with mobility constraints, enhancing arbitrage potential [31].

By pursuing these directions, the proposed IEMS can evolve from a simulation-based prototype to a scalable, field-deployable solution for sustainable residential energy management.

REFERENCES

- [1]. R. El-Azab, "Smart homes: Potentials and challenges," *Clean Energy*, vol. 5, no. 2, pp. 302–315, Jun. 2021, doi: 10.1093/ce/zkab010.
- [2]. B. Risteska Stojkoska and K. Trivodaliev, "A review of Internet of Things for smart home: Challenges and solutions," *J. Clean. Prod.*, vol. 140, pp. 1454–1464, Jan. 2017, doi: 10.1016/j.jclepro.2015.12.116.
- [3]. P. H. Shaikh, N. Mohd. Nor, P. Nallagownden, and I. Elamvazuthi, "Intelligent optimized control system for energy and comfort management in efficient and sustainable buildings," *Procedia Technol.*, vol. 11, pp. 99–106, 2013, doi: 10.1016/j.protcy.2013.12.167.
- [4]. M. U. Hassan, M. H. Rehmani, and J. Chen, "DEAL: Differentially Private Auction for Blockchain-Based Microgrids Energy Trading," *IEEE Trans. Serv. Comput.*, vol. 13, no. 2, pp. 263–275, Mar. 2020, doi: 10.1109/TSC.2019.2947471.
- [5]. E. Shirazi and S. Jadid, "Cost reduction and peak shaving through domestic load shifting and DERs," *Energy*, vol. 124, pp. 146–159, Apr. 2017, doi: 10.1016/j.energy.2017.01.148.
- [6]. M. Marzband, S. S. Ghazimirsaeid, H. Uppal, and T. Fernando, "A real-time evaluation of energy management systems for smart hybrid home Microgrids," *Electr. Power Syst. Res.*, vol. 143, pp. 624–633, Feb. 2017, doi: 10.1016/j.epsr.2016.10.054.
- [7]. M. A. A. Pedrasa, T. D. Spooner, and I. F. MacGill, "Coordinated scheduling of residential distributed energy resources to optimize smart home energy services," *IEEE Trans. Smart Grid*, vol. 1, no. 2, pp. 134–143, Sep. 2010, doi: 10.1109/TSG.2010.2053383.
- [8]. B. Chouaib, D. Lakhdar, and Z. Lokmane, "Smart home energy management system architecture using IoT," in *Proc. ACM Int. Conf. Proc. Ser.*, 2019, pp. 1–6, doi: 10.1145/3361570.3361593.
- [9]. A. Q. H. Badar and A. Anvari-Moghaddam, "Smart home energy management system—a review," *Adv. Build. Energy Res.*, vol. 16, no. 1, pp. 118–143, 2022, doi: 10.1080/17512549.2020.1806925.
- [10]. J. Leitao, P. Gil, B. Ribeiro, and A. Cardoso, "A Survey on Home Energy Management," *IEEE Access*, vol. 8, pp. 5699–5722, 2020, doi: 10.1109/ACCESS.2019.2963502.
- [11]. Z. Zhao and C. Keerthisinghe, "A fast and optimal smart home energy management system: State-space approximate dynamic programming," *IEEE Access*, vol. 8, pp. 184151–184159, 2020, doi: 10.1109/ACCESS.2020.3023665.
- [12]. A. S. Shah et al., "Dynamic user preference parameters selection and energy consumption optimization for smart homes using deep extreme learning machine and bat algorithm," *IEEE Access*, vol. 8, pp. 204744–204762, 2020, doi: 10.1109/ACCESS.2020.3037081.
- [13]. U.S. Energy Information Administration, *Annual Energy Outlook 2022*, 2022.
- [14]. M. Shakeri et al., "An intelligent system architecture in home energy management systems (HEMS) for efficient demand response in smart grid," *Energy Build.*, vol. 138, pp. 154–164, Mar. 2017, doi: 10.1016/j.enbuild.2016.12.026.
- [15]. M. U. Saleem et al., "Integrating Smart Energy Management System with Internet of Things and Cloud Computing for Efficient Demand Side Management in Smart Grids," *Energies*, vol. 16, no. 12, p. 4835, Jun. 2023, doi: 10.3390/en16124835.
- [16]. M. Killian, M. Zauner, and M. Kozek, "Comprehensive smart home energy management system using mixed-integer quadratic-programming," *Appl. Energy*, vol. 218, pp. 299–312, May 2018, doi: 10.1016/j.apenergy.2018.03.179.
- [17]. A. Duman, H. Erden, Ö. Göntül, and Ö. Güler, "A home energy management system with an integrated smart thermostat for demand response in smart grids," *Sustain. Cities Soc.*, vol. 65, p. 102639, Feb. 2021, doi: 10.1016/j.scs.2020.102639.
- [18]. S. Arun and M. Selvan, "Intelligent Residential Energy Management System for Dynamic Demand Response in Smart Buildings," *IEEE Syst. J.*, vol. 12, no. 2, pp. 1329–1340, Jun. 2018, doi: 10.1109/JSYST.2017.2647759.
- [19]. A. Al-Ali, I. Zualkernan, M. Rashid, R. Gupta, and M. Alikarar, "A smart home energy management system using IoT and big data analytics approach," *IEEE Trans. Consum. Electron.*, vol. 63, no. 4, pp. 426–434, Nov. 2017, doi: 10.1109/TCE.2017.015014.
- [20]. J. Li, J. Huang, and P. Zhong, "Intelligent energy management systems for buildings in smart cities using PSO-driven optimization and penalty function constraints," *Int. J. Archit. Comput.*, vol. 23, no. 3, pp. 796–815, Sep. 2025, doi: 10.1177/14780771251362414.
- [21]. F. Alijoyo, "AI-powered deep learning for sustainable industry 4.0 and internet of things: Enhancing energy management in smart buildings," *Alex. Eng. J.*, Jul. 2024, doi: 10.1016/j.aej.2024.07.110.
- [22]. "Hourly solar irradiation data – Helsinki," *Climate-Data.org*. [Online]. Available: <https://en.climate-data.org/europe/finland/uusimaa/helsinki-2355/>.

- [23]. “Electricity spot prices – March 27, 2024,” *Oomi.fi*.
[Online]. Available:
<https://www.oomi.fi/en/electricity/price-information/>.
- [24] “Feed-in tariff for solar power,” *Helen Oy*. [Online].
Available: <https://www.helen.fi/en/electricity/solar-power>.
- [24]. International Energy Agency (IEA), *Residential Appliance Energy Consumption Database*. Paris, France, 2023.

Appendix A: Full List of Appliance Parameters

Table III summarizes the technical and behavioral parameters for all 15 controllable appliances used in the simulation. Power ratings (P_a) are in kW, operating durations (L_a) in hours, and preferred start times (PrefStart $_a$) in 24-hour format. Data were compiled from manufacturer datasheets (Samsung, Jackery, Tineco, etc.) and validated against the IEA Residential Appliance Database [25].

TABLE III Appliance Parameters for MILP-Based IEMS Simulation

Appliance	Type	P_a (kW)	L_a (h)	PrefStart $_a$ (h)
Refrigerator	Fixed	0.15	24	
Router	Fixed	0.01	24	
Desktop PC	Flexible	0.30	8	9
Television	Flexible	0.20	4	19
Electric Kettle	Flexible	2.20	0.2	7.5
Induction Cooker	Flexible	1.80	1.0	12.5
Oven	Flexible	2.00	1.5	18
Washing Machine	Flexible	1.80	1.5	11
Dishwasher	Flexible	1.50	1.2	14
Clothes Dryer	Flexible	2.50	1.0	15
Vacuum Cleaner	Flexible	1.20	0.5	10
Hair Dryer	Flexible	1.60	0.1	7
HVAC	Flexible	Variable	8	6
LED Lighting (Total)	Fixed	0.40	12	
EV Charger	Flexible	3.00	4	2

Note: Fixed appliances operate continuously or on fixed schedules; flexible appliances are subject to MILP scheduling with soft time-window penalties.

Appendix B: Pseudocode of the Optimization Algorithm

The following pseudocode outlines the daily optimization routine executed by the IEMS:

Algorithm 1: Daily MILP-Based Energy Scheduling

Input:

$P_{solar}[1..24]$ // Forecasted solar power (kW)
 $c_{buy}[1..24], c_{sell}$ // TOU prices (€/kWh)
 ApplianceParams // From Table III
 $T_{out}[1..24]$ // Outdoor temperature (°C)
 E_{bat_0} // Initial battery SoC (kWh)

Output:

$x[a,t], y[a,t]$ // Appliance schedules
 $P_{grid_in}[t], P_{grid_out}[t]$ // Grid flows
 $E_{bat}[t]$ // Battery SoC profile

Begin:

1. Initialize MILP model M
2. Add decision variables (Section 5.5)
3. Set objective: minimize $\Sigma (c_{buy}[t]*P_{grid_in}[t] - c_{sell}*P_{grid_out}[t] + \lambda*\delta[t])$
4. Add constraints:
 - a. Energy balance (Eq. 1)
 - b. Battery dynamics (Eq. 2–4)
 - c. Appliance scheduling logic (Eq. 5–7)
 - d. HVAC thermal model (Eq. 8)
 - e. Comfort bounds: $20 \leq T_{in}[t] \leq 24$
 - f. Grid limit: $P_{grid_in}[t] \leq 10$ kW
5. Solve M using Gurobi (MIP gap = 1%, time limit = 300 s)
6. Extract optimal schedules and power flows
7. Return solution

End

Implementation: Python 3.10 + Pyomo + Gurobi 10.0.

Appendix C: Raw Data Sources and URLs

All input data are publicly available or derived from authoritative sources:

- **Solar Generation Profile:**
Climate-Data.org – Hourly solar irradiance for Helsinki, Finland (clear-sky day).
URL: <https://en.climate-data.org/europe/finland/uusimaa/helsinki-2355/>
- **Electricity Buying Prices:**
Oomi.fi – Hourly spot prices for March 27, 2024 (Estonian/Nordic market).
URL: <https://www.oomi.fi/en/electricity/price-information/>
- **Electricity Selling Price:**
Helen Oy – Fixed feed-in tariff for residential solar.
URL: <https://www.helen.fi/en/electricity/solar-power>
- **Appliance Specifications:**
Manufacturer datasheets (Samsung Home Appliances, Jackery Portable Power, Tineco Cleaning Devices).
Aggregated via IEA Energy Efficiency Database:
URL: <https://www.iea.org/data-and-statistics/data-product/energy-efficiency-database>
- **Outdoor Temperature:**
Derived from Helsinki climate normals (Finnish Meteorological Institute).
URL: <https://en.ilmatieteenlaitos.fi/statistics>
- **Grid Connection Limit:**
Standard low-voltage residential connection in EU (10 kW per phase \times 1 phase).

