

A Literature Review of AI-Based Smart Energy Management and Consumption Prediction Systems

Khalsa Gurjyot Kaur¹, Vaishnavi Pagare², Darshana Chaudhary³, Mrs. P. S. Gaidhani⁴

Student, Department of Computer Engineering¹⁻³

Guide, Sr. Lecturer, Department of Computer Engineering²

Guru Gobind Singh Polytechnic, Nashik, India

Abstract: Electricity use in homes, offices, and institutions keeps rising, yet most users cannot easily see which appliances waste energy or how much they will consume next. Research on this problem is spread across several strands: machine-learning (ML) forecasting of consumption, Internet of Things (IoT) energy monitors, appliance-level analysis, home energy management systems (HEMS), recommendation systems, and occupancy-based control. This review analyzes twenty-two publications and one technical report from these strands that are relevant to the AI-Based Smart Energy Management and Consumption Prediction System, a proposed system that combines an energy/current sensor, a presence sensor, a Wi-Fi-enabled microcontroller with a relay module, an ML prediction model, and a web dashboard. Through thematic and comparative analysis we identify four research gaps: forecasting evidence is mostly dataset-based, and the few hardware-linked systems depend on cloud services or heavier edge hardware; prediction-driven control and presence-based control are studied separately; quantified evidence for presence-based control comes mostly from building-scale lighting and HVAC; and recommendation research targets load shifting rather than idle or unnecessary appliance use. We then outline how the proposed system's integrated design is intended to address these gaps. The prototype is under development, so this paper reports no experimental results.

Keywords: Smart energy management, energy consumption prediction, machine learning, Internet of Things, presence detection, appliance control, home energy management system

I. INTRODUCTION

A. Background

Energy consumption in buildings is increasing with social development and urbanization, and forecasting it is regarded as essential for improving energy efficiency and reducing costs and environmental impact [1]. Smart homes add IoT sensing and automation, and the data these sensors generate can be used to model and forecast how energy is consumed [2], [3]. Recent reviews describe AI-driven smart-home energy management as covering forecasting, appliance scheduling, load monitoring, demand response, and control [4], [5]. Three kinds of technology are therefore relevant: sensing and monitoring of consumption, ML-based prediction of future use, and control of appliances. Occupancy information is central to the third, because it shapes how lighting and heating, ventilation, and air-conditioning (HVAC) systems are operated [6].

B. Problem Context

Managing energy is difficult without suitable tools. Users may not know which appliances consume the most energy, may leave appliances switched on when they are not needed, and cannot easily estimate future consumption. Three needs follow. (i) Reliable measurement of consumption, ideally per appliance: IoT monitors that measure current,



voltage, power, and energy over Wi-Fi already exist [7], and non-intrusive load monitoring (NILM) studies how to estimate appliance contributions from an aggregate signal [8], [9]. (ii) Prediction of future consumption: ML forecasting is widely studied [1]–[3], [10]–[12]. (iii) Action: occupancy-based control can reduce unnecessary operation of lighting and HVAC [6], [13]–[15], and recommendations can help households reduce consumption [16]. Most published work addresses one or two of these needs and leaves the others to separate tools.

C. Existing Situation

Existing work falls into five strands. First, ML forecasting studies compare statistical, ensemble, hybrid, and deep-learning models on consumption data [1]–[3], [10]–[12]. Second, IoT prototypes measure electrical quantities and relay them to a cloud, mobile, or server application [7], [17], [18]. Third, appliance-level analysis is pursued mainly through NILM [8], [9]. Fourth, HEMS and recommendation research addresses scheduling, demand response, prediction-based switching, and user advice [16], [19]–[22]. Fifth, occupancy sensing and occupancy-based control are studied mostly at building scale [6], [13]–[15].

D. Limitations of Existing Approaches

A critical reading of the literature reveals four limitations.

1) *Forecasting Evidence Is Mostly Dataset-Based*: Forecasting studies typically report accuracy on recorded or public data: real-time data from a smart grid in an experimental building [1], three public smart-home datasets [11], and household smart-meter datasets [12]. Two systems pair measurement hardware with prediction: an ESP32 monitor with cloud forecasting [7], and an ESP-based device network with a Raspberry Pi server and a Jetson Nano [17]; both rely on cloud services or heavier computing hardware. Reported accuracy values, such as R^2 of 0.999 and 0.997 for heating and cooling load [3] or 99.96% for hourly appliance forecasts [10], are measured on different targets, intervals, and datasets, so they cannot be ranked directly.

2) *Prediction-Driven and Presence-Based Control Are Studied Separately*: Salama and Abdellatif [22] use predicted consumption to switch devices off so that use stays below a threshold, and [17] reports deep-learning prediction together with control and monitoring. Presence-based switching of a load appears in [18], without ML prediction. HEMS reviews cover ML prediction and scheduling largely in cost, price, and grid terms [19], [20], and a meta-review found a bias toward control approaches with little integration of user-centric, information-based solutions [21].

3) *Presence-Based Control Evidence Is Building-Scale*: Savings from occupancy-based control have been analyzed by simulation of lighting and variable-air-volume systems in commercial buildings [15], and occupancy sensing is mostly reviewed at building level [6], [13], [14]. A room-level prototype exists [18], but evidence on how presence events relate to measured consumption and prediction in small deployments is limited.

4) *Recommendations Target Load Shifting*: The recommender in [16] generates activity-shifting schedules to cut emissions or cost, reporting 12% emission and 7% cost savings under an emission focus and 6% and 20% under a cost focus for the households studied. Limited attention has been given to simple recommendations that flag idle or unnecessary appliance use from a low-cost sensor.

E. Motivation

These limitations show that measurement, prediction, control, and advice are each mature enough to demonstrate but are rarely combined in a simple, low-cost form. A system that measures consumption, predicts future use, recommends savings, and switches an appliance off when no person is present, with everything visible on one dashboard, would connect the whole journey from data to action. Building it from commonly available components would also support use in homes, offices, and educational institutions.



F. Proposed Research Direction

The AI-Based Smart Energy Management and Consumption Prediction System is a proposed integrated hardware and software system. On the hardware side, an energy/current sensor measures consumption, a presence sensor detects whether a person is in the monitored area, a Wi-Fi-enabled microcontroller collects the data, and a relay module switches a low-power demonstration appliance. The software, built with Python, Flask, Pandas, NumPy, scikit-learn, SQLite, and a web front end, has two paths: an energy path (sensor data, processing, ML model, energy prediction, smart recommendations, dashboard) and a control path (presence sensor, control logic, relay, appliance, appliance status, dashboard). The prototype is under development, so this paper establishes a literature foundation and does not report experimental results.

G. Objectives

The objectives of this review are: (1) to analyze ML approaches to energy consumption forecasting; (2) to examine IoT energy monitoring and appliance-level analysis; (3) to examine HEMS, prediction-based control, and recommendation research; (4) to examine occupancy sensing and presence-based control; (5) to compare the reviewed studies and identify research gaps; and (6) to position the proposed system relative to those gaps.

H. Scope and Search Strategy

This survey covers research published between 1997 and 2026, with most sources from 2018 onward; the earliest is a foundational sequence-model paper [23]. Sources were identified through web searches of scholarly and institutional repositories (publisher sites, PubMed Central, arXiv, and university repositories) using keyword combinations such as “energy consumption forecasting,” “smart home machine learning,” “ESP32 energy monitoring,” “non-intrusive load monitoring,” “home energy management system,” “occupancy detection PIR,” and “energy saving recommendation.” Studies were selected for relevance to forecasting, monitoring, prediction-based or presence-based control, or user advice, with preference for recent peer-reviewed work. Two arXiv preprints [9], [12], one technical report [15], and one workshop paper [16] are included for topic coverage.

I. Organization of the Paper

Section II presents a thematic literature review in four subsections, followed by a comparative table and an explicit statement of research gaps. Section III concludes with key insights and future directions.

II. LITERATURE REVIEW

The review is organized into four themes: (A) ML-based energy consumption forecasting; (B) IoT monitoring and appliance-level analysis; (C) home energy management systems, prediction-based control, and recommendations; and (D) occupancy sensing and presence-based control.

A. ML-Based Energy Consumption Forecasting

Forecasting studies range from statistical models to ensembles and deep networks. Chou and Tran [1] reviewed ML techniques for forecasting energy time series using real-time data from a smart grid installed in an experimental building, and found that a hybrid model combining forecasting and optimization was more accurate than single and ensemble models. Priyadarshini et al. [2] proposed an ensemble of decision tree, random forest, and gradient boosting models to predict energy consumption in smart homes. Chaganti et al. [3] proposed an ensemble of random forest models for building heating and cooling load, reporting R^2 of 0.999 and 0.997 and investigating the influence of different features. Ambat and Sahoo [11] added an anomaly-detection stage before prediction, testing three outlier-based techniques and several regressors on three public smart-home datasets; cluster-based outlier detection with extreme gradient boosting gave promising results.



At appliance and household level, Devanathan et al. [10] compared eight ML algorithms for appliance-specific forecasting at hourly, daily, weekly, monthly, and quarterly intervals and found that model performance varies with the interval, with a time-series model reaching 99.96% accuracy for hourly forecasts. Emshagin et al. [12] studied short-term household forecasting from smart-meter data using customized LSTM and GRU models, benchmarked against ARIMA, and reported that LSTM performed better than GRU at home level. LSTM networks use gated memory cells to retain information over long sequences [23], which suits consumption time series.

Taken together, these studies agree that ensembles and recurrent networks are strong candidates for consumption forecasting, while the best choice depends on data volume, prediction horizon, and target. Headline accuracy values are not directly comparable, because they are computed on different datasets, targets, and intervals; a new system should therefore compare several models on its own data.

B. IoT Monitoring and Appliance-Level Analysis

Ali et al. [7] built an IoT-powered monitoring framework that measures current, voltage, active power, power factor, and energy in real time on an ESP32, sends the data through the cloud to an Android application, and uses ARIMA, Prophet, and LSTM models to predict future unit consumption; LSTM was the most accurate of the three. Gozuoglu et al. [17] built a Wi-Fi and MQTT network in which ESP-01, NodeMCU, and ESP32 microcontrollers add intelligence to household devices, a Raspberry Pi acts as the home management server, and a Jetson Nano runs a CNN-LSTM model; measurements from an actual house were analyzed and the results for deep learning, control, and monitoring were described as promising. The second system combines sensing, prediction, and control, but it uses more computing hardware than a single microcontroller with a lightweight model.

An alternative to sensing every appliance is NILM, which decomposes an aggregate consumption signal into appliance-level profiles. Kaselimi et al. [8] review NILM for residential appliances and argue for moving disaggregation models toward practical and trustworthy frameworks. Azad et al. [9] review deep-learning NILM methods, summarize public databases, and compare methods using standard metrics. NILM reduces the number of meters needed, but its focus is estimation of appliance contributions rather than closed-loop control. A system that measures a connected load directly obtains appliance-wise data without disaggregation, at the cost of one sensor per monitored load.

C. HEMS, Prediction-Based Control, and Recommendations

Salama and Abdellatif [22] implemented ML and neural-network prediction on an IoT-based smart home energy management system and used the predicted consumption to turn off one or more devices; they report that keeping consumption below a threshold saves the user money over the year. This shows that prediction can drive control, but the trigger is a consumption threshold, not whether anyone is present.

Almughram et al. [19] reviewed ML prediction algorithms in HEMS, covering load forecasting, household consumption prediction, rooftop solar generation, and price prediction, and proposed a HEMS framework based on the most accurate algorithms of earlier studies. Zafar et al. [20] reviewed HEMS concepts, configurations, and technologies, noting that HEMS operate according to criteria such as energy cost, weather, load profiles, and consumer comfort. McIlvennie et al. [21] performed a systematic meta-review of smart-home energy management research and found a bias toward technical, control-oriented approaches and a lack of integration between those approaches and user-centric, information-based solutions. Two recent reviews widen the view: Zafar et al. [4] unify prediction, control, and user-centric management across HVAC and lighting control, appliance scheduling, load forecasting, NILM, and demand response, and identify scalability and data diversity as challenges, while Rokonzaman et al. [5] review AI and IoT-integrated HEMS with solar PV and outline a roadmap that includes hybrid AI-optimization, edge computing, and standardized validation protocols.

On the advice side, Zharova and Löschmann [16] proposed an activity-based multi-agent recommendation system that generates activity-shifting schedules and lets the system focus on emission savings, cost savings, or both. For the households studied, the emission-focused setting produced 12% emission and 7% electricity-cost savings, and the cost-



focused setting produced 6% and 20%. Recommendations are therefore a supported route to savings, but the example reviewed here targets load shifting, not idle or unnecessary use.

D. Occupancy Sensing and Presence-Based Control

Chen et al. [13] reviewed building occupancy estimation and detection, grouping systems by sensor type and comparing sensor fusion. Shokrollahi et al. [6] reviewed passive infrared (PIR) sensor-based occupancy monitoring from 2015 to 2023, covering people counting, activity detection, and localization, and state that occupancy information is critical for shaping energy consumption and optimizing HVAC and lighting. Khan et al. [14] reviewed IoT technologies for occupancy detection and prediction in smart buildings and note that occupancy prediction can optimize the use of building systems.

For quantified savings, a Pacific Northwest National Laboratory study [15] simulated occupancy-based control of lighting and variable-air-volume terminal boxes and found that advanced, people-counting sensors delivered much larger savings than common occupancy sensors. At room scale, Suprianto et al. [18] implemented an ESP32-based IoT system in which a PIR sensor activates the electrical load when a person is present and the reverse when the room is empty, while a mobile screen shows the electricity used and the energy that can be saved.

These works show that presence sensing is a well-established route to reducing unnecessary operation, but the quantified evidence comes from building-level simulation, and the room-level prototype [18] does not combine presence-based control with ML prediction. A further design consideration, which none of the reviewed prototypes quantifies, is how often a presence sensor wrongly switches an appliance off while a person is still present; this should be tested explicitly.

The comparison of these studies is summarized in Table I.

TABLE I: Comparative Analysis of Reviewed Studies in Energy Forecasting, Monitoring, Control, and Occupancy Sensing

Ref.	Year	Approach / Technology	Main Contribution	Key Finding	Limitation
[1]	2018	Single, ensemble, and hybrid ML models on real-time smart-grid data from an experimental building	Review and comparison of ML forecasting of energy time series	Hybrid model more accurate than single and ensemble models	Building-level data; forecasting only; no control
[2]	2022	Ensemble of decision tree, random forest, and gradient boosting	Ensemble prediction of energy use in smart homes	Ensemble proposed for smart-home power prediction	Prediction only; no sensing hardware or control
[3]	2022	Ensemble of random forest models on building energy data	Heating and cooling load prediction and feature influence	R^2 of 0.999 (heating) and 0.997 (cooling)	Targets building load, not appliance-wise usage
[4]	2026	PRISMA systematic review of AI for smart-appliance optimization	Unifies prediction, control, and user-centric management	Identifies scalability and data diversity as challenges	Review; no system built
[5]	2026	Review of AI and IoT-integrated HEMS with solar PV	Forecasting, optimization, scheduling, and demand-side management	Roadmap: hybrid AI-optimization, edge computing, standardized validation	Review; PV and grid oriented



Ref.	Year	Approach / Technology	Main Contribution	Key Finding	Limitation
[6]	2024	Review of PIR-based occupancy monitoring (2015–2023) and ML	People counting, activity detection, localization	Occupancy information shapes energy use, HVAC, and lighting efficiency	Review; no appliance-level system
[7]	2023	ESP32 sensing, cloud, Android app; ARIMA, Prophet, LSTM	IoT energy monitor with AI-based unit prediction	LSTM more accurate than ARIMA and Prophet	Monitoring and prediction only; no appliance control
[8]	2022	Review of NILM using signal processing, ML, and deep learning	Challenges and perspectives for trustworthy NILM	Need to move toward practical, trustworthy frameworks	Review; no system built
[9]	2023	Review of deep-learning NILM methods	Compares NILM methods and public databases	Summarizes databases and compares methods on standard metrics	Review; no system built
[10]	2026	Eight ML algorithms; hourly to quarterly horizons; appliance-level	Appliance-specific forecasting across time intervals	Best model depends on interval; time-series model reached 99.96% accuracy hourly	Forecasting only; hardware and control not described in abstract
[11]	2025	Outlier-based anomaly detection followed by RF, LR, DT, AdaBoost, GB, XGBoost	Anomaly detection plus forecasting for smart-home devices	Cluster-based outlier factor with XGBoost gave promising accuracy on three public datasets	Public datasets; no hardware or control
[12]	2022	LSTM and GRU compared with ARIMA on household smart-meter data	Short-term household-level forecasting	LSTM performed better than GRU for home-level forecasting	Dataset-based; no hardware or control
[13]	2018	Review of occupancy estimation and detection by sensor type	Categorizes sensors and sensor-fusion systems	Sensor fusion widely adopted	Review; building-level scope
[14]	2024	Review of IoT-based occupancy prediction in smart buildings	Technologies, methods, and future directions	Occupancy prediction can help optimize building systems	Review; building-level scope
[15]	2013	Simulation of occupancy-based control for lighting and VAV systems	Savings of common vs. advanced occupancy sensors	Advanced (counting) sensors give larger savings than common sensors	Simulation; commercial buildings
[16]	2023	Activity-based multi-agent recommender system	Recommendations for cutting emissions or cost in households	12% emission and 7% cost savings (emission focus); 6% and 20% (cost focus)	Load-shifting focus; not sensor-driven control
[17]	2024	ESP-based devices, MQTT, Raspberry Pi server, Jetson Nano CNN-LSTM	Deep-learning energy estimation with control and monitoring	Promising results on actual house measurements	Heavier hardware; presence-based control not described in abstract



Ref.	Year	Approach / Technology	Main Contribution	Key Finding	Limitation
[18]	2023	ESP32 with PIR sensor, load switching, and power monitoring	IoT room automation and power monitoring	Load activated when a person is detected; energy used and saved shown on phone	No ML prediction or recommendations
[19]	2022	Review of ML prediction algorithms in HEMS	Covers load, household, solar, and price prediction; proposes a framework	Supports model selection for consumption prediction	Review; prediction-centred
[20]	2020	Review of HEMS concepts, configurations, technologies	Overview of HEMS computing and communication trends	HEMS operate on cost, weather, load, and comfort criteria	Review; grid and demand-response oriented
[21]	2020	Systematic meta-review of smart-home energy management research	Maps impacts, agents, and functions of SHEMS	Bias toward techno-centric control; little integration with user-centric information	Review; identifies integration gap
[22]	2022	AIoT smart-home energy management; ML and neural-network power prediction	Prediction-based switching of devices to limit consumption	Keeping consumption below a threshold reported to save the user money	Trigger is a consumption threshold; presence not described in abstract
[23]	1997	Long short-term memory (gated recurrent memory)	Sequence model for long-term dependencies	Basis of LSTM models used for consumption forecasting	General-purpose; needs labeled sequences

E. Identified Research Gaps

Synthesizing the reviewed literature reveals four research gaps. Each follows the pattern: existing studies have addressed X; however, limited attention has been given to Y.

1) *What existing research has achieved:* ML models forecast consumption with high reported accuracy on defined datasets [1]–[3], [10]–[12]; an ESP32 monitor with cloud forecasting [7] and a multi-device network with deep-learning prediction, control, and monitoring [17] have been demonstrated; prediction has been used to switch devices off [22]; NILM estimates appliance-level profiles from aggregate signals [8], [9]; HEMS and recommender research address scheduling and user advice [4], [5], [16], [19]–[21]; and occupancy sensing is well reviewed and shows savings in simulation [6], [13]–[15], with a room-level ESP32 prototype available [18].

2) *What remains insufficient:* Despite these advances, four gaps remain.

Gap 1 (Forecasting Is Mostly Dataset-Based): Forecasting is evaluated mostly on recorded or public datasets [1], [11], [12], and the hardware-linked systems use cloud services [7] or a Jetson Nano and Raspberry Pi [17]; limited attention has been given to lightweight models trained and tested on data from a low-cost current sensor in the same system that uses the predictions.

Gap 2 (Prediction-Driven and Presence-Based Control Are Separate): Control is triggered by predicted consumption [22], or reported alongside deep-learning prediction without a described presence trigger [17], while presence-based switching appears without ML prediction [18]; limited attention has been given to one workflow in which presence-based switching, measured consumption, prediction, and recommendations share a single dashboard.



Gap 3 (Presence-Based Control Evidence Is Building-Scale): Quantified savings come from building-level simulation [15] and reviews [6], [13], [14]; limited attention has been given to presence-controlled single appliances whose ON/OFF events are logged alongside measured consumption, including analysis of wrongly triggered switch-offs.

Gap 4 (Recommendations Target Load Shifting): Recommender research targets shifting activities to cheaper or cleaner periods [16]; limited attention has been given to simple recommendations that point out idle or unnecessary appliance use from low-cost sensor data.

3) *Why that limitation matters:* Without integration, users need separate tools to measure, predict, advise, and control. Control without a link to measurement cannot show what was saved, prediction that is not connected to action does not change behavior, and results from simulation or public datasets may not carry over to a small deployment with noisy low-cost sensors. The reviews themselves point to limited real-world validation and weak integration of control with user-facing information [4], [5], [21].

4) *How the proposed system addresses these gaps:* The system is designed as one workflow with four elements: (a) a prediction module trained on consumption data from the prototype's own current sensor, with lightweight candidate models compared using regression metrics such as MAE, RMSE, and R^2 , addressing Gap 1; (b) a single microcontroller and dashboard that carry the energy path and the control path, so that presence events, measured consumption, predictions, and recommendations appear together, addressing Gap 2; (c) a presence sensor and relay whose ON/OFF events are shown as appliance status next to measured consumption, with testing proposed for wrongly triggered switch-offs, addressing Gap 3; and (d) recommendations derived from analysis of high or unnecessary consumption patterns, addressing Gap 4. The overall workflow follows the project proposal; the model-comparison metrics and the switch-off reliability tests are proposed validation steps. All of these must be validated experimentally.

III. CONCLUSION

This review analyzed twenty-two publications and one technical report on ML-based energy forecasting, IoT monitoring, appliance-level analysis, home energy management, prediction-based control, recommendations, and occupancy-based control. ML forecasting reports high accuracy on defined datasets, IoT monitors and multi-device systems with prediction and control have been demonstrated, and occupancy sensing shows savings in simulation. However, these strands remain largely separate: forecasting evidence is mostly dataset-based, prediction-driven and presence-based control are studied separately, quantified presence-based evidence is building-scale, and recommendations target load shifting rather than idle use.

The proposed AI-Based Smart Energy Management and Consumption Prediction System responds by integrating energy sensing, ML prediction, smart recommendations, presence detection, relay-based appliance control, and a web dashboard in one workflow. Because the prototype is under development, the claims in this paper concern the literature and the design rationale only.

Future work should focus on three directions: (1) comparing classical, ensemble, and recurrent models, including LSTM [7], [12], [23], on data from the prototype and on larger, more diverse datasets; (2) extending the system to more appliances and sensors, with anomaly detection [11] and, where fewer meters are desired, NILM-style disaggregation [8], [9]; and (3) the planned extensions of mobile application support, electricity bill estimation, advanced analytics, and real-time notifications, together with explicit testing of presence-sensor reliability.

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