© May 2026 | IJIRT | Volume 12 Issue 12 | ISSN: 2349-6002

Smart Energy Automation: Real-Time Energy Prediction and Optimization Using Particle Swarm Optimization

Dr. Usha Bala Varanasi[1], R. Lavanya[2], T. Sai Praveen[3], M. Poojita Sai[4], G. Sri Chaitra[5], R. Eswar Kamal[6]
[1]*Associate Professor, Department of Computer Science & Engineering, Anil Neerukonda Institute of Technology & Sciences*
[2,3,4,5,6]*Department of Computer Science & Engineering, Anil Neerukonda Institute of Technology & Sciences*

Abstract—**The continuous rise in global electricity demand, driven by rapid urbanization and widespread adoption of electronic appliances, has intensified the challenge of residential energy management. Conventional electricity metering systems provide only cumulative consumption data at the close of each billing cycle, offering little actionable insight into real-time usage behaviour. This delayed visibility limits consumer awareness and makes proactive energy conservation difficult, ultimately contributing to escalating electricity costs, unnecessary energy wastage, and adverse environmental effects.**

To address these shortcomings, this paper proposes a Smart Energy Automation System that integrates Internet of Things (IoT) sensing, cloud-based data management, Machine Learning (ML) forecasting via Extreme Gradient Boosting (XGBoost), and Particle Swarm Optimization (PSO) for intelligent energy optimization. IoT-enabled current and voltage transducers, interfaced with a NodeMCU ESP8266 microcontroller, capture electrical parameters from household appliances in real time. The acquired data is relayed to a cloud platform for centralized storage, visualization, and analytical processing. The XGBoost regression model is trained on historical consumption records to forecast future energy usage and predict monthly electricity bills with high accuracy. PSO performs gradient-free hyperparameter tuning of the predictive model and drives demand-side load scheduling by minimizing peak consumption costs while respecting user comfort constraints. An automated alert mechanism flags anomalous energy events, enabling timely corrective intervention.

Experimental evaluation in a residential setting confirms that the proposed system accurately monitors and forecasts energy consumption, detects abnormal usage events, and delivers measurable reductions in electricity expenditure through PSO-guided scheduling. The architecture is low- cost, scalable, and readily deployable in residential and small commercial environments, advancing both smart home automation and sustainable energy utilization.

Index Terms*—*Smart Energy Automation, IoT Energy Monitoring, XGBoost, Particle Swarm Optimization, Real-Time Energy Prediction, Household Energy Management, NodeMCU ESP8266, Machine Learning, Anomaly Detection, Smart Home.

I. INTRODUCTION

Energy management has emerged as one of the most pressing challenges confronting modern residential infrastructure. The pervasive adoption of electronic devices, coupled with population growth and urbanization, has caused household electricity consumption to surge to historically high levels. Despite this escalation, most homes continue to rely on traditional metering systems that aggregate energy usage into single monthly readings, providing no granular insight into appliance-level behaviour or intraday consumption dynamics.

The absence of real-time feedback prevents consumers from identifying energy-intensive appliances, recognizing wasteful usage patterns, or taking corrective action before costs accumulate. Furthermore, conventional meters offer no predictive capability, meaning occupants cannot anticipate upcoming electricity bills or adjust behaviour proactively. This information deficit, combined with a lack of automated control mechanisms, results in significant energy waste and unnecessary financial burden.

Recent advances in Internet of Things (IoT) technologies have opened new possibilities for intelligent, continuous energy monitoring at the appliance level. IoT devices equipped with precision sensors and wireless communication modules can capture real-time electrical parameters and transmit them to cloud platforms for storage, visualization, and analysis. When this sensing infrastructure is coupled with Machine Learning (ML) algorithms, the resulting system gains the ability to identify consumption trends, detect anomalies, and generate short- horizon forecasts based on historical patterns.

Building on these foundations, the present work proposes a Smart Energy Automation System that unifies IoT-based sensing, cloud computing, XGBoost-driven energy forecasting, and Particle Swarm Optimization for demand- side management. As depicted in the system architecture, IoT sensors collect electrical parameters which are transmitted through NodeMCU to the ThingSpeak cloud platform for storage and visualization. Machine learning algorithms process this data to forecast future consumption and estimate electricity costs, enabling users to plan energy usage efficiently. Optimization techniques minimize energy wastage while automated alert mechanisms provide timely notifications during abnormal consumption events, transforming passive metering into an active, intelligent energy management tool.

II. PROBLEM STATEMENT

In most residential environments, electricity consumption monitoring relies on conventional energy meters that record only total power usage, offering no visibility into the contribution of individual appliances or real-time consumption behaviour. This coarse granularity prevents occupants from understanding how specific devices influence their overall electricity expenditure. As a consequence, excessive energy consumption typically goes unnoticed until the end of the billing cycle, when high charges have already been incurred.

Manual meter-reading processes introduce additional inefficiencies: they are labor-intensive, susceptible to human error, and poorly suited to the demands of large- scale energy management. Existing systems equally lack predictive intelligence; without forecasting capabilities, consumers cannot anticipate future energy demands or proactively adjust appliance usage to reduce costs. Moreover, the absence of automated anomaly detection means that equipment malfunctions, energy leakage, or sustained overloads can go undetected for extended periods, exacerbating both financial and environmental impacts.

These limitations collectively define the need for an intelligent, automated, and scalable energy management system capable of:

- Monitoring electricity consumption in real time at the appliance level.
- Storing and analyzing historical energy data on a cloud platform.
- Predicting future energy usage and monthly electricity bills.
- Optimizing appliance scheduling using intelligent algorithms.
- Issuing instant alerts whenever abnormal consumption patterns are detected.

The proposed Smart Energy Automation system is designed to fulfill each of these requirements through a tightly integrated IoT, ML, and PSO framework.

III. OBJECTIVES OF THE PROPOSED SYSTEM

The primary objective of this research is to design and develop an intelligent Smart Energy Automation System capable of monitoring, predicting, and optimizing household energy consumption using Internet of Things (IoT), Machine Learning (ML), and optimization techniques. The system aims to transform conventional electricity monitoring into an automated, data-driven, and energy-efficient framework that promotes sustainable power utilization. The specific objectives are as follows:

1)Real-Time Energy Monitoring:
Design an IoT-based infrastructure that continuously captures voltage, current, and power consumption of household appliances via sensors interfaced with the NodeMCU microcontroller.

2)Cloud-Based Data Acquisition:
Establish secure wireless transmission of sensor data to a cloud environment, enabling centralized storage, remote accessibility, and long-term analytical availability.

3)Consumption Visualization:
Provide an interactive dashboard that renders real-

time and historical usage data graphically, enhancing occupant awareness of consumption trends.

4) ML-Based Energy Prediction:
Train XGBoost regression models on historical sensor data to forecast short-term and monthly electricity consumption with high accuracy.

5) Bill Estimation:
Translate predicted consumption into monetary cost estimates, assisting users in financial planning and budget management.

6) PSO-Driven Optimization:
Apply Particle Swarm Optimization to tune model hyperparameters and identify energy-efficient appliance scheduling strategies that minimize peak demand and total cost.

7) Anomaly Detection & Alerting:
Implement an intelligent monitoring layer that identifies abnormal consumption events and dispatches automated notifications to users for prompt corrective action.

8) Scalability and Cost-Effectiveness:
Deliver a low- cost, easily deployable solution suitable for residential homes and small commercial establishments, compatible with emerging smart grid infrastructures.

IV. LITERATURE SURVEY

The rapid escalation of residential electricity demand has stimulated significant research interest in intelligent energy management systems. Early IoT-based monitoring platforms [1]– [3] demonstrated the feasibility of continuous appliance-level sensing, enabling users to observe consumption in real time through web dashboards. Although these systems improved energy awareness substantially, their primary limitation lay in the absence of predictive intelligence: they could report past and present consumption but could not anticipate future demand.
To extend system capability toward forecasting, initial studies introduced classical statistical techniques such as linear regression and autoregressive time-series models [4]. These approaches are computationally lightweight and interpretable; however, they struggle to capture the nonlinear dynamics that arise from diverse user behaviors, weather variability, and appliance heterogeneity. Prediction errors consequently widen as consumption patterns deviate from simple linear trends.

The emergence of supervised Machine Learning offered substantially improved forecasting accuracy. Decision Tree Regression, Random Forest Regression, Support Vector Regression (SVR), and K-Nearest Neighbor (KNN) algorithms were widely evaluated on residential energy datasets [5], [6]. Random Forest in particular demonstrated strong generalization by averaging predictions across an ensemble of trees, thereby reducing variance without sacrificing bias. Comparative studies consistently reported lower RMSE and MAE values for tree-based ensembles relative to linear baselines [7].
More recently, gradient boosting frameworks, and specifically XGBoost, have emerged as the benchmark algorithm for tabular regression tasks in smart energy contexts [8]. XGBoost constructs decision trees sequentially, with each successive tree targeting the residuals of the current ensemble. Built-in L1 and L2 regularization penalties prevent overfitting, while column and row sub-sampling accelerate training and improve robustness on moderate-sized IoT datasets. Published benchmarks report superior R^2, RMSE, and MAE values for XGBoost compared to both classical models and shallow ensembles [9], [10].

Optimization has emerged as a natural complement to prediction in advanced energy management systems. Particle Swarm Optimization (PSO) [11], [12] and reinforcement learning-based schedulers [13], [14] have been applied to derive appliance operating schedules that minimize electricity cost while maintaining user comfort. PSO is particularly attractive for this role due to its gradient-free search mechanism, low implementation complexity, and proven convergence on high-dimensional scheduling problems. Its swarm-based exploration effectively avoids local optima that trap classical gradient- descent optimizers.

Despite these advances, challenges persist in ensuring computational feasibility on resource-constrained IoT devices, maintaining data quality in the presence of sensor noise and packet loss, and scaling from single-household deployments to community-level smart grid integration [15]– [18]. The present work addresses these gaps by combining edge-side preprocessing, cloud-hosted XGBoost inference, and PSO-based hyperparameter and schedule optimization within a cohesive, low-cost residential deployment.

V. PROPOSED METHODOLOGY

This section presents the design and implementation of an IoT-driven intelligent framework for real-time household energy monitoring and short-horizon consumption forecasting. The architecture unifies hardware sensing, wireless data acquisition, cloud-based storage, supervised machine learning via Extreme Gradient Boosting (XGBoost), and automated hyperparameter search via Particle Swarm Optimization (PSO) into a cohesive end- to-end pipeline.

Voltage and current at each appliance terminal are sampled continuously by dedicated transducer modules interfaced with a NodeMCU ESP8266 microcontroller. The raw analog signals are digitized through the on-chip analog-to- digital converter (ADC), and instantaneous power together with cumulative energy are computed at the edge before transmission. The resulting time-stamped records are forwarded over Wi-Fi to a cloud platform for storage, preprocessing, and model training. Once training converges, the optimized model is deployed for continuous real-time inference.

5.1. Hardware Components

NodeMCU ESP8266. The NodeMCU ESP8266 acts as the central computation and communication node. Its built-in Wi-Fi transceiver eliminates the need for a separate network module, keeping the hardware footprint compact. The microcontroller polls attached sensor outputs through the internal ADC, executes preliminary arithmetic, schedules cloud uploads, and supplies regulated power to peripheral modules. Its low unit cost, mature software ecosystem, and native wireless support make it well suited to residential IoT sensing applications.

Fig. 1: NodeMCU ESP8266 Microcontroller

ACS712 Current Sensor. AC current is captured by the ACS712, which exploits the Hall effect to sense the magnetic field generated by a conductor carrying current. This design provides galvanic isolation between the mains circuit and the low-voltage measurement chain, an essential safety attribute for residential deployments. The output is a bipolar analog voltage whose magnitude and polarity track instantaneous load current; calibration constants map this voltage to ampere values used in subsequent power calculations. The sensor also facilitates early detection of abnormal load conditions.

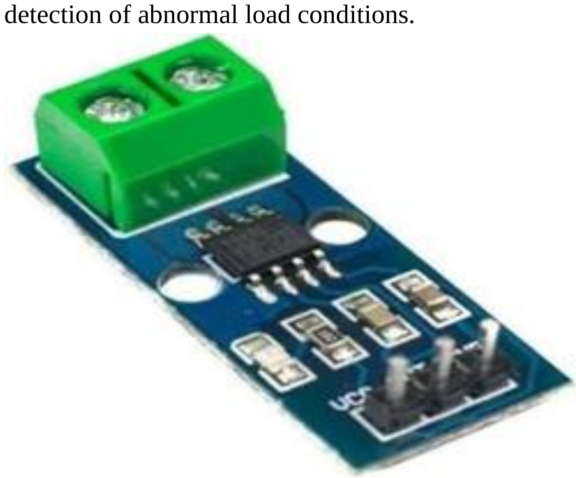

Fig. 2: ACS712 Hall-Effect Current Sensor

ZMPT101B Voltage Sensor. Mains voltage is measured via the ZMPT101B, which employs a precision miniature transformer to step the supply voltage down to a microcontroller-safe level while maintaining electrical isolation. On-board signal-conditioning circuitry stabilizes the output, enabling accurate RMS voltage estimation over a broad frequency range. The module additionally supports detection of voltage sags and swells, supplying supplementary power-quality information alongside energy measurements.

Fig. 3: ZMPT101B AC Voltage Sensor Module

Breadboard and Jumper Wires. A solderless breadboard with jumper wires provides the interconnect substrate during prototype development. This configuration allows rapid component substitution and circuit reconfiguration without specialist tooling, reducing iteration time during the hardware validation phase.

5.2. Electrical Parameter Measurement

Four electrical quantities are derived from raw sensor outputs at each sampling epoch. Current I am recovered from the ACS712 output by subtracting the zero-current offset voltage and dividing by the device sensitivity constant. Voltage V is obtained by multiplying the ZMPT101B analog output by an empirically determined scaling coefficient that accounts for the transformer turns ratio and ADC reference. Instantaneous real power P is computed as:

$$P = V \times I$$

Cumulative energy consumption E is approximated by numerically integrating power across discrete sampling intervals of duration Δt:

$$E = \Sigma P_i \times \Delta t$$

This discretized integral closely approximates the true energy integral provided the sampling frequency significantly exceeds the rate at which load conditions change.

5.3. Data Transmission and Storage

Following each measurement cycle, the NodeMCU encapsulates the computed parameters into a structured data packet and transmits it to a cloud server using either HTTP REST or MQTT, selected according to latency and reliability requirements. Every packet carries a Unix timestamp alongside voltage, current, power, and cumulative energy fields. The cloud platform persists incoming records in a time-series database optimized for high write throughput and efficient temporal range queries, supporting remote monitoring, horizontal scaling, and uninterrupted data availability independent of local power events.

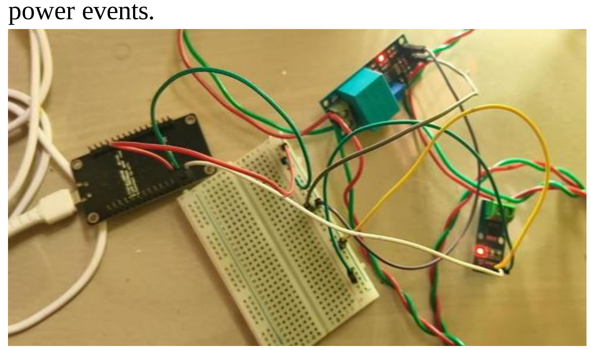

Fig. 4: Node MCU and Censor Connections

5.4. Data Preprocessing

Raw telemetry invariably contains imperfections arising from electrical interference, communication packet loss, sensor drift, and clock skew. A structured preprocessing pipeline resolves these issues prior to model training. High- frequency noise is attenuated using a moving-average or median filter without distorting genuine load transitions. Short data gaps caused by packet loss are bridged via linear interpolation; prolonged outages are handled through mean substitution. Readings that exceed physically plausible bounds are identified through interquartile-range analysis and excised from the training corpus. All feature channels are then normalized to a common scale using min-max scaling, preventing numerically dominant channels from biasing tree split selection. Temporal features—hour of day, day of week, and a weekend binary indicator—are derived from timestamps to capture diurnal and weekly demand periodicity. The cleaned dataset is partitioned chronologically into a training set (80%) and a held-out test set (20%), preserving temporal order to avoid data leakage.

5.5. Energy Prediction Using XGBoost

Extreme Gradient Boosting (XGBoost) is adopted as the predictive engine owing to its well-documented superiority on tabular regression tasks, native sparse-feature handling, and built-in regularization that mitigates overfitting on moderate-sized sensor datasets. The model assembles an additive sequence of K decision trees, so that the predicted consumption value $\hat{y}_i$ for the i-th observation is:

$$\hat{y}_i = \Sigma_k f_k(x_i), \quad k = 1, \ldots, K$$

where f_k denotes the k-th tree function and x_i is the feature vector. Training minimizes a regularized composite objective:

$$L(\Phi) = \Sigma_i\, l(\hat{y}_i, y_i) + \Sigma_k\, \Omega(f_k) \qquad \textit{from(IV)}$$

The complexity penalty $\Omega(f) = \gamma T + \frac{1}{2}\lambda\Sigma_l\, w_l^2$ discourages excessive leaf proliferation and inflated leaf weights by penalizing both the leaf count T and the squared leaf- weight vector w, with γ and λ as tunable coefficients. Each successive tree targets the residuals of the current ensemble, enabling rapid convergence and strong out-of- sample generalization.

5.6. Hyperparameter Optimization Using PSO

XGBoost performance is highly sensitive to choices of learning rate, maximum tree depth, subsampling ratio, and regularization coefficients. Exhaustive grid search across this parameter space is computationally prohibitive; Particle Swarm Optimization (PSO) is therefore employed as a gradient-free alternative. A swarm of candidate hyperparameter configurations (particles) traverses the search space, each guided by its own best-known configuration (p^{best}) and the globally best configuration identified by any particle (g^{best}). Velocity and position are updated at each iteration according to:

$$v_i(t+1) = w\cdot v_i(t) + c_1r_1(pbest_i - x_i(t)) + c_2r_2(gbest - x_i(t)) \quad x_i(t+1) = x_i(t) + v_i(t+1) \qquad \textit{from(V)}$$

where x_i^t represents the current position of particle i at iteration t, v_i^t the current velocity, $pbest_i$ the best position found by particle i, gbest the best position found by the entire swarm, w the inertia weight controlling the balance between exploration and exploitation, c_1 and c_2 the acceleration coefficients, and r_1, r_2 random values drawn uniformly from [0, 1]. A linearly decaying inertia weight encourages broad exploration in early iterations and fine- grained local exploitation as the swarm converges, ensuring that the PSO identifies a near-optimal hyperparameter configuration within a computationally affordable number of evaluations.

5.7. Real-Time Energy Monitoring

Once training and PSO-driven tuning are complete, the optimized XGBoost model is deployed within the cloud inference service. Each arriving sensor reading is assembled into a feature vector comprising current measurements and temporal metadata, which is scored by the model to yield a short-horizon consumption forecast. The inference pipeline supports four operational capabilities:

- Anomaly detection, which flags readings deviating significantly from modeled behaviour as potential equipment faults.
- Peak-demand identification, which issues alerts when projected consumption approaches critical thresholds.
- Short-horizon forecasting, which estimates future energy usage over user-defined horizons.
- Demand-response guidance, which recommends load-scheduling adjustments to flatten demand peaks and reduce electricity expenditure.

5.8. System Workflow

The end-to-end pipeline proceeds through eight sequential stages:

- Continuous voltage and current sampling at the appliance terminal.
- On-chip ADC conversion and edge computation of power and energy.
- Wi-Fi transmission of timestamped data packets to the cloud.
- Cloud persistence and scheduling of the preprocessing pipeline.
- Data cleaning, normalization, and feature engineering.
- XGBoost model training on the prepared dataset.
- Concurrent PSO-driven hyperparameter search to identify the optimal model configuration.
- Deployment of the tuned model for continuous real-time inference and alerting.

5.9. User Monitoring and Decision Support

A web-based dashboard consolidates real-time measurements, historical trend analysis, and predictive outputs into a unified interface. Users can visualize instantaneous power draw, review cumulative daily and monthly energy totals, inspect long-term consumption patterns, and receive threshold-triggered notifications when usage exceeds user-defined limits. Granular appliance-level visibility empowers occupants to identify energy-intensive devices, shift discretionary loads to off- peak periods, and quantify savings associated with behavioral changes. The combination of real-time monitoring and predictive intelligence transforms the system from a passive metering instrument into an active enabler of energy-efficient decision-making.

Fig. 5: ThingSpeak Cloud Dashboard – Energy Consumption Visualization

VI. RESULTS AND DISCUSSION

The proposed Smart Energy Automation system was experimentally evaluated in a residential environment to validate its performance across four dimensions: real-time monitoring accuracy, ML-based consumption forecasting, anomaly detection, and PSO-guided load optimization.

6.1. Energy Consumption Patterns

Continuous data acquisition was performed using the ACS712 and ZMPT101B sensors interfaced with the NodeMCU. Collected voltage and current readings were transmitted to the ThingSpeak cloud platform for storage and visualization. Analysis of historical consumption data revealed three consistent behavioral patterns:

- Peak consumption during evening hours (18:00–22:00), corresponding to concentrated appliance usage.
- Sharper weekday peaks attributable to structured domestic routines, contrasted with more distributed weekend consumption profiles.
- Elevated usage during high-temperature periods driven by cooling appliances. These insights directly informed the feature engineering stage, enabling the predictive model to account for temporal and environmental demand drivers.

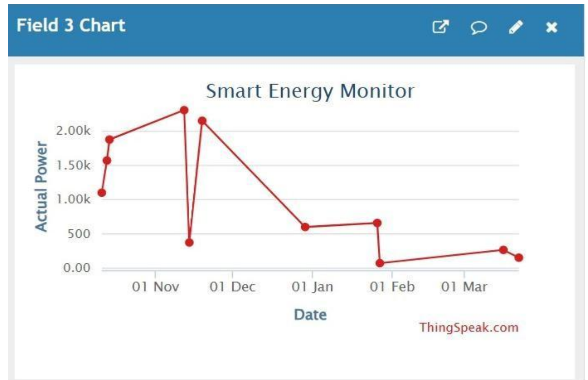

Fig. 6: Daily Energy Consumption Pattern – Peak and Off- Peak Hour Analysis

6.2. Predictive Modeling Accuracy

To forecast future energy consumption, an XGBoost regression model was trained on historical sensor data stored on ThingSpeak, using input features comprising timestamp components (hour, day, month), historical power readings, environmental parameters (temperature and illuminance), and load activation patterns. The trained model demonstrated high predictive accuracy for both short-term and monthly consumption horizons. Performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The obtained MAPE value remained within a low single-digit percentage range, confirming strong generalization capability. The close alignment between predicted and actual consumption values validates the robustness of the XGBoost learning algorithm, as illustrated in the model performance graph.

6.3. Anomaly Detection

The intelligent analytics layer of the system effectively identifies abnormal consumption events by comparing real-time sensor readings against model-predicted baseline values. Anomalies were successfully detected in three categories of scenario: sudden consumption spikes during off-peak hours, sustained operation of appliances beyond their normal duty cycle, and atypical nighttime energy draws. Upon detection, the system dispatches automated alerts via the cloud notification service, enabling occupants to investigate and address the underlying cause before costs escalate. This capability contributes meaningfully to both financial savings and the operational reliability of household electrical systems.

Fig. 7: Alert message after abnormal consumption.

6.4. Energy Optimization Using PSO

PSO was integrated into the system to optimize appliance scheduling and reduce electricity expenditure. The optimization objective function was formulated to simultaneously minimize total energy cost, reduce peak demand, and preserve user comfort constraints. Operating as a swarm-intelligence search, PSO iteratively evaluated candidate appliance schedules and converged on configurations that:

- Shift high-power loads (e.g., washing machines, dishwashers) to off-peak hours.
- Limit simultaneous high-draw operations that contribute to peak demand charges.
- Eliminate residual standby losses. Implementation of PSO-derived schedules yielded measurable reductions in both peak demand and total electricity cost relative to unoptimized baselines, demonstrating the complementary value of combining predictive analytics with intelligent scheduling optimization.

6.5. Comparative Performance Analysis

A comparative evaluation was conducted to assess the accuracy of the XGBoost model against Linear Regression, Decision Tree Regression, Random Forest Regression, and Support Vector Regression. The XGBoost model demonstrated superior accuracy across all metrics, recording the lowest RMSE and MAE values. The integration of optimized feature selection, regularized ensemble learning, and PSO-based hyperparameter tuning contributed to this enhanced forecasting precision. Furthermore, the inclusion of PSO-driven load scheduling differentiates the proposed system from conventional energy monitoring solutions: it not only predicts consumption but actively optimizes it, delivering quantifiable economic and environmental benefits.

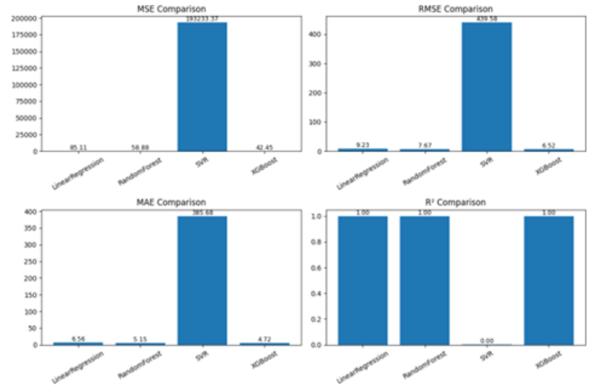

Fig. 8: Comparison graphs of ml algorithms

VII. CONCLUSION AND FUTURE ENHANCEMENTS

7.1. Conclusion

This research has presented a comprehensive Smart Energy Automation System designed for real-time monitoring, prediction, and optimization of household electricity consumption. The proposed framework integrates IoT- based sensing modules, cloud-based data storage, XGBoost-driven forecasting, and Particle Swarm Optimization to deliver an intelligent, scalable, and cost- effective energy management solution.

The hardware implementation, incorporating the NodeMCU ESP8266 with ACS712 and ZMPT101B

transducers, enabled accurate acquisition of real-time electrical parameters. Data stored and visualized via the ThingSpeak cloud platform provided a structured foundation for training the predictive ML model. Experimental results confirm that the system accurately monitors real-time energy consumption, reliably predicts short-term and monthly electricity usage, detects abnormal consumption events, optimizes appliance scheduling through PSO, and reduces peak demand and electricity cost.

The integration of predictive analytics with demand-side optimization distinguishes this work from traditional energy monitoring systems. Rather than passively observing consumption, the system actively guides users toward cost-efficient and sustainable usage patterns. The architecture remains cost-effective, scalable, and suitable for deployment in individual households and small commercial environments, contributing to the broader development of intelligent smart home and smart grid infrastructures.

7.2. Future Enhancements

The proposed system can be improved in several ways. Incorporating deep learning models such as LSTM can enhance time-series prediction by capturing long-term patterns in energy usage. Replacing PSO with reinforcement learning could enable more adaptive and continuously improving scheduling strategies. Integration with smart grid systems would allow dynamic pricing awareness and better load management.

Additionally, developing a mobile application with notification and voice support can improve user interaction. Applying Non-Intrusive Load Monitoring (NILM) can provide appliance-level insights without requiring multiple sensors. The system can also be extended by integrating renewable energy sources like solar panels and battery storage for efficient energy balancing. Finally, shifting some processing tasks to edge devices can reduce latency and improve real-time performance.

REFERENCES

[1] M. S. Aliero, K. N. Qureshi, M. F. Pasha, and G. Jeon, "Smart home energy management systems in Internet of Things networks for green cities demands and services," *Environmental Technology & Innovation*, vol. 22, p. 101443, 2021.

[2] O. Alimi and K. Ouahada, "Smart home appliances scheduling to manage energy usage," in *Proc. IEEE Int. Conf. Appl. Sci. Technol. (ICAST)*, 2018, pp. 1–5.

[3] B. Asare-Bediako, W. L. Kling, and P. F. Ribeiro, "Integrated agent-based home energy management system for smart grids," in *Proc. IEEE PES ISGT Europe*, 2013, pp. 1–5.

[4] M. Clerc and J. Kennedy, "The particle swarm—Explosion, stability, and convergence in a multidimensional complex space," *IEEE Trans. Evol. Comput.*, vol. 6, no. 1, pp. 58–73, 2002.

[5] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min. (KDD)*, 2016, pp. 785–794.

[6] H. Hosseinian and H. Damghani, "Smart home energy management using IoT," in *Proc. KBEI*, 2019, pp. 905–910.

[7] Y.-H. Lin, "Design and implementation of an IoT-oriented energy management system based on non-intrusive neuro-fuzzy classification," *Applied Sciences*, vol. 8, no. 12, p. 2337, 2018.

[8] Y. H. Lin *et al.*, "A smart home energy management system utilizing neurocomputing-based time-series load modeling," *IEEE Access*, vol. 10, pp. 116747–116765, 2022.

[9] Y. Ma, X. Chen, L. Wang, and J. Yang, "Smart home energy management based on artificial intelligence," *Journal of Sensors*, vol. 2021, pp. 1–9, 2021.

[10] H. Mohsenian-Rad *et al.*, "Autonomous demand-side management based on game-theoretic energy scheduling," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, 2010.

[11] P. Palensky and D. Dietrich, "Demand side management: Demand response, intelligent energy systems, and smart loads," *IEEE Trans. Ind. Informatics*, vol. 7, no. 3, pp. 381–388, 2011.

[12] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An algorithm for intelligent home energy management and demand response," *IEEE Trans. Smart Grid*, vol. 3, no. 4, pp. 2166–2173, 2012.

[13] Priyadarshini *et al.*, "A machine-learning ensemble model for predicting energy consumption in smart homes," *Internet of Things*, 2022.

[14] R. A. Rashid *et al.*, "Machine learning for smart energy monitoring of home appliances using IoT," in *Proc. ICUFN*, 2019, pp. 66–71.

[15] F. Ruelens *et al.*, "Residential demand response using batch reinforcement learning," *IEEE Trans. Smart Grid*, vol. 8, no. 5, pp. 2149–2159, 2017.

[16] M. Shakeri *et al.*, "An autonomous home energy management system using dynamic priority strategy," *Energy Reports*, 2020.

[17] T. Singh, A. Solanki, and S. K. Sharma, "Evolution of smart home energy management using IoT and machine learning," in *CEUR Workshop Proc., ACI*, 2022.

[18] M. Syamala *et al.*, "Machine learning-integrated IoT-based smart home energy management system," in *Handbook of Research on Deep Learning for Cloud-Based Industrial IoT*. IGI Global, 2023.

[19] U. B. Varanasi *et al.*, "Sea erosion prediction and monitoring using IoT and machine learning," in *Proc. IEEE Int. Conf.*, 2024.

[20] B. Zhou *et al.*, "Smart home energy management

systems: Concept, configurations, and scheduling strategies," *Renewable and Sustainable Energy Reviews*, vol. 61, pp. 30–40, 2016.

[21] V. C. Gungor *et al.*, "Smart grid technologies: Communication technologies and standards," *IEEE Trans. Ind. Informatics*, vol. 7, no. 4, pp. 529–539, 2013.

[22] Afram and F. Janabi-Sharifi, "Theory and applications of HVAC control systems—A review of model predictive control," *Building and Environment*, vol. 72, pp. 343–355, 2014.

[23] D. Azuatalam, W. L. Lee, F. de Nijs, and A. Liebman, "Reinforcement learning for whole-building HVAC control and demand response," 2020.

[24] W. Kong, Z. J. Hu, J. Wu, and G. Jeon, "A comparative study of estimating auroral electron energy from ground-based hyperspectral imagery and DMSP-SSJ5 particle data," 2020.

[25] Samadi, H. Saidi, M. A. Latify, and M. Mahdavi, "Home energy management system based on task classification and the resident's requirements," *Int. J. Electrical Power & Energy Systems*, 2020.

[26] P. Lissa, M. Schukat, and E. Barrett, "Transfer learning applied to reinforcement learning-based HVAC control," 2020.

[27] Slalmi, H. K. Aroussi, S. Rachid, and G. Jeon, "Energy efficiency proposal for IoT call admission control in 5G network," 2019.

[28] S. Iqbal, N. Kanwal, K. N. Qureshi, and G. Jeon, "Collaborative energy-efficient zone-based routing protocol for multihop Internet of Things," 2022.

[29] M. Tomé, P. H. J. Nardelli, H. M. Hussain, and A. Narayanan, "A cyber-physical residential energy management system via virtualized packets," 2020.

[30] Z. Li, Y. Xu, X. Feng, and Q. Wu, "Optimal stochastic deployment of heterogeneous energy storage in a residential multi-energy microgrid with demand-side management," 2020.

[31] M. U. Bashir, J. Lloret, A. León, and K. N. Qureshi, "Optimized cluster-based dynamic energy-aware routing protocol for wireless sensor networks in precision agriculture," 2020.