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SMARTWATT NEXUS

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Abstract:
Electricity consumers and utility operators increasingly require systems that move beyond retrospective billing and provide timely, actionable intelligence. This paper presents SMARTWATT NEXUS, an AIoT-based platform that integrates real-time electricity data ingestion, anomaly-aware analytics, and short-horizon consumption forecasting within a single deployment-oriented architecture. The platform supports dual ingestion paths: secure IoT API uploads and Zigbee2MQTT stream subscriptions. To handle field heterogeneity, the backend normalizes multiple payload formats, including cumulative energy values and power-only readings, with automatic conversion of instantaneous power samples to energy estimates. Forecasting is performed using a hybrid model stack that includes Long Short-Term Memory (LSTM), a regression ensemble based on Linear Regression and Random Forest Regressor, and an Artificial Neural Network (ANN). The system also includes automated meter-to-user association, health observability endpoints, dashboard analytics, and engagement mechanisms such as badges and recognition workflow. Implementation-level evaluation demonstrates stable ingestion behavior, successful handling of mixed telemetry schemas, reliable alert generation for abnormal usage, and continuous forecast availability after minimal historical data accumulation. The proposed framework offers a practical, extensible baseline for intelligent residential and institutional energy management.

Keywords: AIoT, smart energy, electricity forecasting, Zigbee2MQTT, anomaly detection, LSTM, ANN, IoT analytics.

I. INTRODUCTION

The transition toward intelligent energy ecosystems requires digital systems that can sense, interpret, and respond to consumption behavior in near real time. Traditional monthly billing workflows provide delayed visibility and are inadequate for demand-aware decisions at household and institutional levels. As energy cost sensitivity and load variability continue to increase, users need systems that not only track usage but also forecast future demand and detect abnormal patterns early.

SMARTWATT NEXUS was developed to address this need with a practical engineering focus. The system combines IoT telemetry ingestion, machine learning prediction, anomaly-triggered alerts, and user-facing analytics in one integrated platform. Unlike many academic prototypes that assume ideal sensor outputs, this implementation handles real deployment conditions where devices may report in different formats or omit direct energy counters. The result is a resilient pipeline that remains operational even under heterogeneous device behavior.
This paper presents the final implementation architecture, core algorithms, recent robustness enhancements, and practical observations from integrated execution.

II. RELATED WORK

Research in smart energy analytics has broadly evolved along three tracks: IoT-based metering infrastructure, machine learning for load forecasting, and user feedback systems for demand-side optimization. Existing studies demonstrate that real-time sensing and predictive analytics can reduce energy waste and support better load planning.

Classical approaches commonly use regression models for interpretable forecasting under structured data assumptions. Deep learning approaches, particularly sequence models such as LSTM, improve temporal pattern modeling when historical trends are nonlinear or seasonally variable. In parallel, IoT-centric frameworks improve data granularity but often face practical constraints related to payload inconsistency, protocol variation, and deployment complexity.

Many available systems remain fragmented, with data collection, prediction, and user action loops implemented as loosely connected modules. SMARTWATT NEXUS addresses this gap through a deployment-driven, end-to-end design that couple's ingestion resilience, runtime observability, forecasting continuity, and user engagement.

III. PROBLEM DEFINITION AND DESIGN GOALS

Three recurring issues motivated this work:

1. Ingestion fragility in heterogeneous IoT environments.

Field devices do not always provide standardized payloads. Some report kWh directly, while others provide Wh or only instantaneous power.

2. Weak coupling between forecasting and live operations.

In many prototypes, predictions are generated offline and are not integrated with real-time ingestion events.

3. Limited user impact after analytics.

If systems stop at raw charts, users receive visibility but not sustained behavioral cues.

Based on these gaps, the platform was designed with the following goals:

1. Robust multi-format data ingestion.
2. Integrated and continuous prediction pipeline.
3. Real-time anomaly signaling.
4. Runtime observability for deployment confidence.
5. User-oriented feedback mechanisms to promote energy awareness.

IV. SYSTEM ARCHITECTURE

SMARTWATT NEXUS follows a layered architecture shown conceptually as sensing, communication, Intelligence, and application layers.

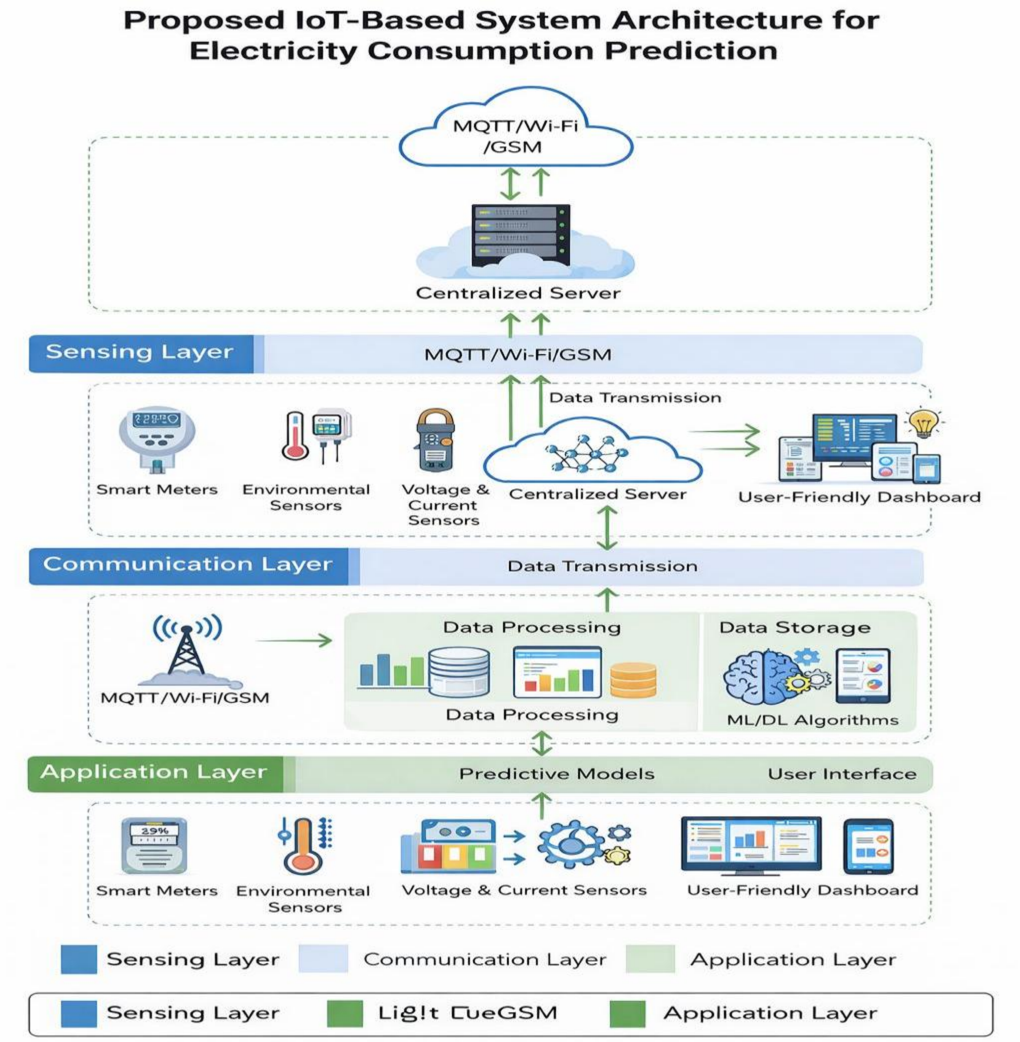

FIG: SYSTEM ARCHITECTURE

A. Sensing and Edge Layer

Smart meter nodes and microcontroller-based clients collect consumption values and transmit readings periodically. Zigbee-enabled devices can publish to broker topics compatible with Zigbee2MQTT conventions.

B. Communication Layer

Two communication paths are supported:

1. HTTPS IoT API path: devices post meter-linked consumption payloads to the backend.2. MQTT subscription path: backend subscribes to Zigbee2MQTT topics and ingests accepted messages directly.

The dual-channel design improves flexibility and reduces dependency on a single transport path.

C. Intelligence and Processing Layer

The backend performs:

1. Payload parsing and normalization.
2. Meter identity resolution from payload fields and topic suffix.
3. Optional auto-binding of unknown meter identities to eligible users.
4. Consumption extraction from kWh keys, Wh keys, and power-only keys.

5. Best-effort anomaly checks and forecast generation after ingestion.

D. Application and Observability Layer

The application layer provides:
1. Dashboard, daily usage, prediction, report, and bill-estimation views.
2. Alert notifications for high-consumption deviations.
3. Health endpoints for service state, database state, and Zigbee subscriber status.
4. Engagement features including badges and recognition workflow.

V. METHODOLOGY

A. Data Handling Strategy

Incoming records are validated and normalized before persistence. The system accepts multiple key patterns for energy values. If cumulative energy is unavailable but instantaneous power is provided, energy is estimated using the sampling interval.

Let P be power in watts and Delta t be sample duration in seconds. Estimated energy in kilowatt-hour is:

E_{kWh} = \frac{P \cdot \Delta t}{3,600,000}

This conversion enables interoperability with low-cost sensors and incomplete payloads.

B. Forecasting Models

The forecast subsystem uses three implemented predictors:

1. LSTM Predictor

Captures short-range temporal dynamics from recent consumption windows.

2. Regression Ensemble Predictor

Combines Linear Regression and Random Forest Regressor outputs.

3. ANN Predictor

Uses dense nonlinear mapping for trend approximation.

A combined estimate is reported as arithmetic mean:

\hat{y}_{avg} = \frac{\hat{y}_{LSTM} + \hat{y}_{REG} + \hat{y}_{ANN}}{3}

Fallback logic is included to preserve prediction availability when heavy dependencies are not active.

C. Anomaly Signaling

The system computes a user-specific recent baseline and triggers high-consumption alerts when current usage exceeds a threshold over that baseline. This supports immediate behavioral intervention.

VI. IMPLEMENTATION DETAILS

The final implementation uses a Flask-based backend with SQLAlchemy persistence, frontend templates for analytics views, and utility modules for machine learning operations.

Recent implementation updates that improve originality and deployment quality include:
1. Direct Zigbee detection and mapping from topic/payload identifiers.
2. Auto-bind workflow for user-meter assignment when identifiers are not pre-registered.
3. Power-only telemetry conversion into estimated kWh samples.
4. Health database information endpoint with entity counts and path visibility.
5. Continuous ingestion-to-prediction trigger path.
6. User engagement extension via badges and recognition flow.

These updates were introduced to solve practical field challenges rather than only improving offline model behavior.

VII. RESULTS AND DISCUSSION

This work reports implementation-consistent operational observations from integrated project runs.

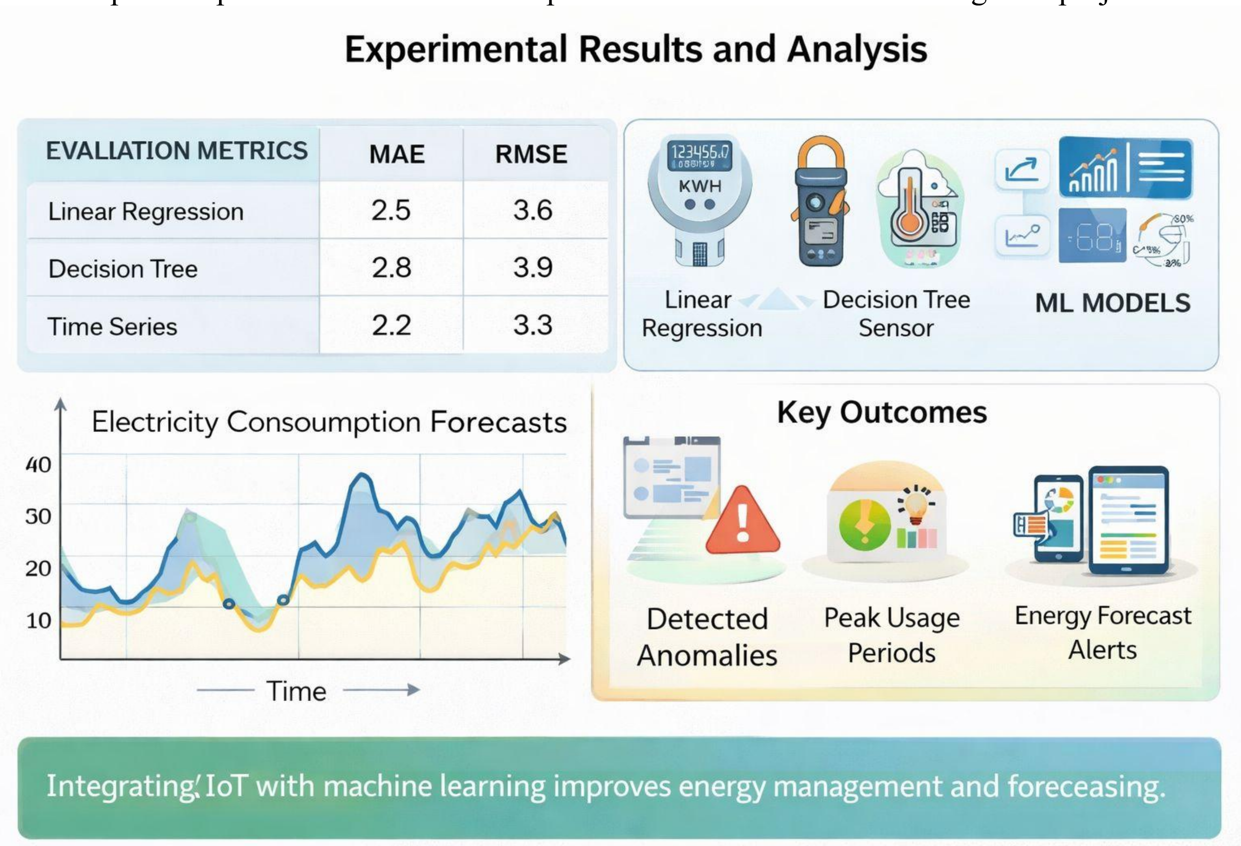

FIG: RESULTS

A. Ingestion Reliability

Both API-based and MQTT-based pipelines ingest records successfully under configured settings. The system handles mixed payload structures without interrupting core workflow.

B. Forecast Continuity

After sufficient record history is available, the model stack generates next-day predictions and stores per-model outputs with aggregate estimate.

C. Anomaly Responsiveness

High-consumption events over recent user baseline trigger alert generation, enabling early awareness.

D. Operational Transparency

Health endpoints provide service and database visibility, and Zigbee runtime status improves diagnostic speed during deployment.

E. Practical Impact

The platform supports actionable energy awareness for users while maintaining extensibility for institutional or smart-campus scale adaptation.

VIII. CONCLUSION

SMARTWATT NEXUS demonstrates that practical AIoT energy systems must prioritize ingestion robustness and operational continuity as much as forecasting accuracy. By integrating dual communication paths, resilient payload normalization, adaptive meter association, multi-model prediction, anomaly signaling, and health observability, the platform provides a complete and field-relevant electricity intelligence workflow. Recent implementation enhancements further improve heterogeneity tolerance and deployment readiness. The final system establishes a credible foundation for scalable smart energy management in real-world settings.

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