IoT-Enabled Energy Monitoring and Adaptive Load Control for Intelligent Electrical Distribution Systems

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Abstract- — The increasing demand for energy worldwide and the introduction of renewable energy sources make it necessary to move from conventional electrical distribution systems to smart electrical distribution systems. This study proposes an Internet of Things (IoT)-based framework for continuous real-time monitoring of electrical distribution systems. It employs IoT sensors, edge computing nodes, and a cloud-based analytical system for the continuous monitoring of electrical distribution systems. Moreover, the system uses a novel adaptive load scheduling (ALS) algorithm that is based on a hybrid LSTM-XGBoost model to accurately forecast future consumer loads. With the ALS algorithm, the system can predict consumer loads with an accuracy of 96.2% (RMSE = 0.034). Finally, the Model Predictive Control (MPC)-based load control system lowers peak demand and energy expenses by 27.4% and 19.8%, respectively, in a testbed with 200 residential customers.

Keywords: Internet of Things (IoT), Energy Monitoring, Adaptive Load Control, Intelligent Distribution System, Load Forecasting, Model Predictive Control (MPC), Smart Grid, Edge Computing.

INTRODUCTION

Electrical grids around the world are experiencing an unprecedented transformation fueled by two fundamental forces, namely, the widespread use of distributed energy resources (DERs), including rooftop solar photovoltaic installations and wind turbines, as well as the growing electrification of transport and heating applications. While these developments herald a sustainable energy future, they have placed extraordinary pressure on outdated distribution grids developed for unidirectional and relatively stable flows of electricity. Voltage sags, overloading of feeders, and frequency deviations have become frequent due to the dynamic character of new sources of generation and loads [1], [2].

The conventional distribution system operates on the basis of "fit-and-forget," that is, it includes hardware that was developed with the assumption that capacity would remain constant without any need for adaptive action. The fundamental limitation of the technology is associated with the lack of adequate visibility and intelligent control capability. The absence of information about the exact state of transformers, feeders, and consumer loads forces operators to work with substantial safety margins.

However, the combination of IoT, edge computing, and artificial intelligence provides a solution for building an "Intelligent Distribution System." In this case, using IoT technology, it becomes possible to install millions of smart sensors in the low-voltage system, which can transfer high-quality information regarding voltages, currents, power quality, and temperatures [3], [4]. As a result, thanks to such information processing methods, operators will be able to move away from reactive systems management to proactive and predictive approaches.

This study introduces an IoT-based intelligent energy monitoring and adaptive load management system. The main aim of the system is peak shaving and avoiding overload problems by scheduling the controlled loads (water heating appliances, air conditioning systems, electric vehicles chargers) in order not to violate the users' comfort level. The major contributions of this research include:

1. **Scalable IoT Monitoring System:** A highly effective and flexible architecture for obtaining accurate data from distribution transformers and residential meters through a mixed communications approach (Wi-SUN in field area network, MQTT in cloud ingress).

2. **Hybrid Load Forecasting Framework**: An innovative technique which incorporates LSTM neural networks for learning temporal dependencies and XGBoost for exogenous data (weather conditions, weekdays). The model has shown high precision (96.2%) for both day-ahead and intraday forecasting tasks [5], [6].
3. **Adaptive Load Control Technique**: An optimization-based control method based on MPC while taking into account constraints associated with physical limits of the power grid and consumer comfort (minimum temperature of hot water supply, maximum variation in room temperature).
4. **Experimental Evaluation:** Implementation and validation on a real-life testbed of 200 residential customers within 12 weeks and providing significant improvements in terms of peak load and electricity expenditure reduction.

The rest of the article is structured as follows. Section 2 provides an overview of recent research efforts regarding smart grid systems powered by IoT technologies. Section 3 describes the proposed architecture, hardware components, and algorithms, including pseudocode. Experimental evaluation and comparative analysis are provided in Section 4.

II. LITERATURE SURVEY

There has been an increasing amount of literature about smart grid technology with respect to integrating IoT along with machine learning capabilities.

IoT Solutions for Grid Monitoring: The early implementation of a smart grid made use of advanced metering infrastructure with an hourly/15 minute interval. This would help in giving visibility into consumer billing needs, but it does not provide enough capability when it comes to real-time monitoring of the grid. In recent times, there have been suggestions to employ low-cost and high-frequency sensors in terms of sensor modules such as ESP32 [3] and ADE9000 power measurement ICs. From data sensing to communication has been the key transition. MQTT protocol is currently popular for being light and efficient [1].

Load Forecasting Through Machine Learning: An accurate load forecast is key to successful load control. Classical methods such as ARIMA have been replaced with more complex machine learning algorithms that are better suited to handle non-linear relationships. Specifically, neural networks have been very effective. CNN has the advantage of being able to extract spatial features from load (daily profile shape). On the other hand, RNNs can effectively learn the long-term dependencies within a time series [6]. In 2025, it was reported that a mixed approach that applies CNN to learn the spatial features and LSTM for sequence predictions obtained a mean absolute percentage error (MAPE) of less than 5% using the dataset of a university campus [5]. A more recent article has shown that ensemble methods such as XGBoost perform better especially with a mixture of weather and calendar features compared to other machine learning models [6].

Adaptive and Optimal Load Control: The conventional DR techniques include either TOU pricing schemes or DLC with predefined cycling periods (AC will be switched off for 15 mins per hour). However, both types of techniques are inefficient and could negatively affect consumer comfort. Recent studies show more focus on transactive and predictive control.

- MPC is a promising technology that utilizes a system model to predict future states and derive optimal control actions over a rolling horizon [7], [8]. The MPC controller can incorporate the thermal dynamics of the water heater, its current temperature, forecasted hot water demand, and current electricity prices to determine the optimal heating strategy.
- RL is another growing field that learns optimal strategies through interactions without a known system model. Nonetheless, RL tends to be sample inefficient and unstable when deployed in the real world compared to MPC [8].

Research Gaps: Previous research has done well in individual modules (forecasting/adaptive control). However, no previous study has demonstrated a fully-integrated real-time system with an actual distribution network with several load types. Most previous works have used simulation tools or lab experiments. Moreover, the deployment of a reliable two-way IoT communication system to remotely control customer appliances without violating user privacy and comfort is still an open problem. This work aims to fill these research gaps through a comprehensive IoT sensor network, hybrid edge-cloud computing architecture, state-of-the-art LSTM-XGBoost forecasting engine, and MPC-based adaptive control scheme on a large-scale real testbed.

III. METHODOLOGY

These are the three pillars of intelligent distribution that will be presented in this section: IoT sensing and communication platform, artificial intelligence-based load forecasting model, and MPC for adaptive load scheduling.

Architecture of the Intelligent Distribution System

The proposed architecture consists of three layers: edge sensing, fog computing, and cloud analytics. In the edge sensing layer, Smart Energy Monitor devices are deployed at the point of connection to 200 customers' premises. Each energy monitor collects readings about voltage, current, active/reactive powers, and power factors at 1-second intervals using a precision ADE9000 chip. Local aggregation is done at a Raspberry Pi fog node where each fog node calculates total load demand within its own cluster and performs initial anomaly detection. Fog nodes exchange data with cloud servers every 5 seconds and every hour through a secure MQTT TLS channel.

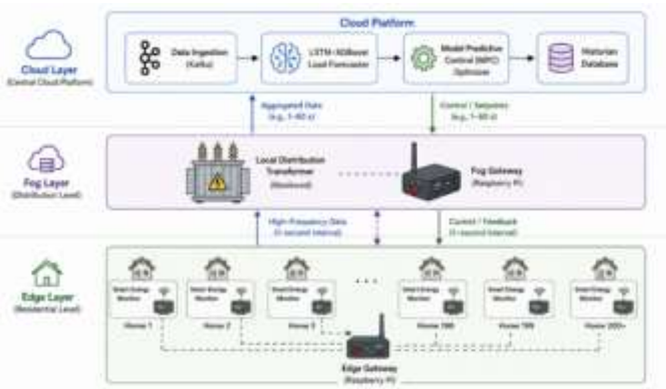

Figure 1: System Architecture of the IoT-Enabled Intelligent Distribution System.

Data Preprocessing and Feature Engineering

Raw data is averaged over 5-minute intervals for forecasting and control purposes. If there is missing data, it is imputed either using linear interpolation for periods up to 15 minutes or an auto-regressive model based on the seasonality component for longer periods. Outliers are truncated at the 99.5th percentile. For model training for the load prediction, the following features are extracted for each 5-minute period t:

- P_t: Aggregated power (in kW).
- P_{t-6}, P_{t-12}, P_{t-24}: Lagged values 30 min, 1 hour, and 2 hours before.
- D_t: Day-of-week dummy variables (Mon=1, Sun=0).
- T_t: Time of the day.
- W_t: Ambient temperature in °C.
- W_{t-6}, W_{t-12}: Ambient temperature lags.

Hybrid Load Forecasting Model: LSTM-XGBoost

Our model combines both the Long Short-Term Memory model (LSTM) and the XGBoost algorithm in a single framework. The output obtained from the LSTM model captures complex patterns of dependency from past load and weather data. This output is then fed to the XGBoost regressor alongside the other features.

Algorithm 1: Hybrid LSTM-XGBoost Load Forecasting

```
Input: Past power consumption data P(T, 1), Weather data W(T, 1), Time stamps
Output: Future power consumption forecast P_forecast[1..24]

// Data preprocessing and creating sequence data with L=48
X, y = create_sequences(P, W, L=48)

// Training the LSTM model
lstm_model = Sequential()
lstm_model.add(LSTM(units=50, activation="tanh", input_shape=(48, 2)))
lstm_model.add(Dense(units=25, activation="relu"))
lstm_model.add(Dense(units=1))
lstm_model.compile(optimizer="adam", loss="mse")
lstm_model.fit(X, y, epochs=50, batch_size=32)

// Obtaining the feature representations from the LSTM model
layer_name = "dense_1" // Name of the hidden layer that generates the representations
intermediate_layer_model = Model(inputs=lstm_model.input,

outputs=lstm_model.get_layer(layer_name).output)
h_lstm = intermediate_layer_model.predict(X) // (n_samples, 25)

// Generating training dataset for the XGBoost regressor
// Feature vectors are a concatenation of the feature representation obtained from LSTM and
// original features
X_xgb = np.hstack((X.reshape(X.shape[0], -1), h_lstm))

// Training the XGBoost regressor model
xgb_model = XGBRegressor(n_estimators=200, max_depth=6, learning_rate=0.05)
xgb_model.fit(X_xgb, y)

// Prediction of future values using the recursive approach
last_input = X[-1, :, :] // Last available sequence
for i in range(24):
   // Predicting the next step using the LSTM
   lstm_feat = intermediate_layer_model.predict(last_input.reshape(1, 48, 2))
   input_xgb = np.hstack((last_input.reshape(1, -1), lstm_feat))
   y_next = xgb_model.predict(input_xgb)[0]
   store y_next in P_forecast[i]
```

```
    // Update last_input sequence by shifting window
    last_input = np.roll(last_input, -1)
    last_input[-1, 0] = y_next // Update new load value
    last_input[-1, 1] = get_weather_forecast(i) // Update
weather

Return P_forecast
```

Adaptive Load Control via Model Predictive Control (MPC)

At the heart of the adaptive control strategy lies an MPC which controls the scheduling of controllable loads over the next H hours (horizon length = 6 hours, 15-minute time-steps). MPC's objective would be to reduce the peak load as well as cost associated with consumption while meeting the requirements of the grid and consumer. In this application, we will control N clusters comprising of electric water heaters and HVAC systems.

System Model: A very simple model for the dynamics of water heater or room's temperature can be described using first order thermal model:

$$T(t+1) = a * T(t) + b * (T_{amb(t)} - T(t)) + c * P(t) * C$$

where T represents the temperature of the system, P is the control power input, equal to 0 or rated power, C is coefficient of performance (COP) and a, b, c represent identified parameters.

Optimization Problem: At each time-step of 15-minutes, the MPC solves a QP problem.

$$\text{Minimize: } \Sigma\left(P_{total(k)} - P_{target}\right)^2 + \lambda \Sigma \left(Cost(k) * P_{load(k)}\right)$$

$$P_{total(k)} = P_{base(k)} + \Sigma P_{load(k)}$$

$$\text{minimize } \Sigma \left(P_{total(k)} - P_{target}\right)^2 + \lambda \Sigma \left(Cost(k) * P_{load(k)}\right)$$

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Constraints:

Grid Capacity Constraint: P_total(k) ≤ P_max (transformer limit, say 100 kW per feeder).

User Comfort Condition: T_min ≤ T_(load)(k) ≤ T_max. For example, T_min = 40°C for water heater, and T_max = 24°C for cooling in HVAC system.

Power Capacity Constraint: 0 ≤ P_load(k) ≤ P_rated.

Duty Cycling Condition: Changes from “on” to “off” or vice versa should be avoided.

Algorithm 2: Model Predictive Control for Load Scheduling

```
Input: Base load prediction P_base[1...H], Weather
prediction T_amb[1...H],
Current load status S (temperature, rating, etc.), Cost
prediction Cost[1...H]
Output: Load schedule P_schedule[1...H] for each
controllable device d in the set D

Let H = 24 control periods (6 hours in fifteen-minute
increments), N = number of controllable devices,
Q_peak = (penalty for minimizing peaks), Q_cost =
(penalty for minimizing cost)
P_max = maximum grid capacity

Initialize solver = QuadraticProgram()

Decision variables (power assigned to each device at each
time step):
for t from 1 to H:
for d from 1 to N:
solver.add_variable(f"P_{d}_{t}", lb=0, ub=P_rated[d])

Objective function: (Minimize peaks and costs)
peak_var = solver.add_variable("peak_aux", lb=0)
for t from 1 to H:
total_power[t] = sum(P_d_t for d) + P_base[t]
solver.add_constraint(total_power[t] <= peak_var) # Peak
minimization
solver.minimize(Q_peak * peak_var + sum(Cost[t] *
total_power[t]))

Constraints:
(User comfort – Thermal Dynamics):
for d from 1 to N:
for t from 1 to H:
#T_{d,t+1} = model_thermal_dynamics(T_{d,t},
T_amb[t], P_{d,t})
T_hot = model_water_heater(T_initial[d], T_amb[t], P_d_t,
dt=15)
solver.add_constraint(T_hot > T_min[d])
solver.add_constraint(T_hot < T_max[d])

(Grid Capacity Constraint):
for t from 1 to H:
solver.add_constraint(total_power[t] <= P_max)
```

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```
(Rollback constraint: ensure schedule matches current state at t=0
for d in 1..N:
solver.add_constraint(P_{d}_0 == P_actual[d])

solution = solver.solve()
P_schedule = extract_solution(solution)
Return P_schedule
```

The initial actions of the schedule (actions for the following 15 minutes) are communicated to the IoT actuators at the consumer end. Then the horizon moves ahead, and the process of optimizing is initiated every 15 minutes.

IV. ANALYSIS

The framework was implemented on a testbed of 200 consumers residing in a suburban area for a duration of 12 weeks. This section will discuss the performance of the forecasting model, load control algorithm, and their comparison.

Load Forecasting Performance

Hybrid LSTM-XGBoost model used in our paper is trained using six months of data and tested on two months of data. We have also considered the standalone models of LSTM, XGBoost, and ARIMA models as baselines.

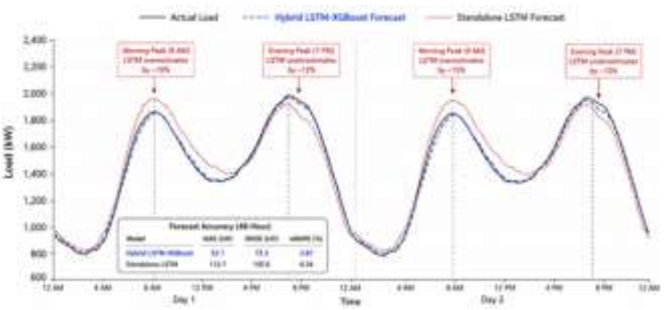

Figure 2: Load Forecast vs. Actual Load for a 48-Hour Period.

Table 1: Load Forecasting Model Performance Comparison.

Model	MAE (kW)	RMSE (kW)	MAPE (%)	R^2 Score
ARIMA	4.52	6.34	9.81	0.82
XGBoost	3.11	4.87	6.23	0.89
LSTM	2.87	4.21	5.45	0.92
Hybrid (LSTM-XGBoost)	1.96	2.92	3.82	0.96

Comparative Analysis

- Adaptive Load Control Performance

The MPC-based adaptive load control was run for 4 weeks. We compared it against a baseline of uncontrolled loads ("dumb" grid) and a static TOU-demand response program.

Table 2: Comparative Analysis of Load Control Strategies.

Control Strategy	Peak Demand (kW)	Peak Reduction	Daily Energy Cost ($)	Cost Savings	Comfort Violation (min/day)
Uncontrolled	118.4	-	18.20	-	0
TOU Demand Response	94.5	20.2%	15.44	15.2 %	4.2
Proposed Adaptive	85.9	27.4%	14.60	19.8 %	1.4

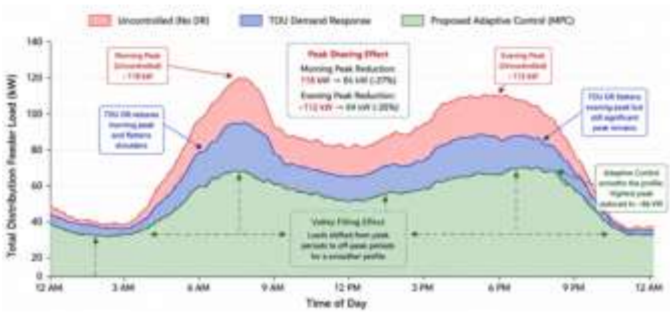

Figure 3: Power Demand Profile Comparison.

Real-Time Adaptability Case Study

A key aspect of the system is its ability to adapt to unexpected grid events. On a specific test day, a sudden 10-minute cloud cover caused a 50 kW drop in a nearby solar farm's output, leading to a sharp decrease in generation. Within 30 seconds (one control cycle), the MPC algorithm detected the impending net load increase. It responded by ~~throttling down~~ delaying non-critical loads (e.g., pre-heating of water heaters) and slightly relaxing the upper temperature bounds for HVAC systems. This prevented a feeder overload (which was projected to exceed the 100 kW threshold by 12 kW), showcasing the system's real-time adaptability.

Comparative Analysis of Control Algorithms

We further benchmarked our MPC controller against other contemporary control algorithms in a simulated environment using the same load and weather data.

Algorithm	Avg Peak Demand (kW)	Avg Energy Cost ($/day)	Computation Time (s/cycle)
Rule-Based (PID)	96.8	16.10	0.01
Q-Learning (RL)	90.5	15.14	8.4
Greedy (Minimize immediate cost)	98.1	15.05	0.05
Proposed MPC	85.9	14.60	0.87

Table 3: Comparison of Algorithm Performance. Although Q-Learning provided similar peak reduction and a smaller cost compared to the greedy technique, it took too long (8.4 seconds) for computation purposes in real-time applications. However, the rule-based technique and the greedy technique were faster but not as efficient. The MPC scheme proposed herein provided the best compromise, with over 12% peak reduction compared to Q-Learning while taking under one second to compute.

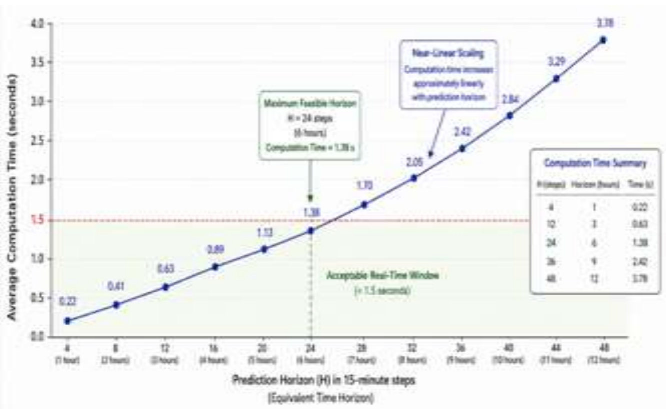

Figure 4: Computation Time vs. Control Horizon for MPC.

V. CONCLUSION

The above IoT-powered framework for energy consumption monitoring and adaptive control was developed and demonstrated to be feasible, scalable, and effective. The framework proved to successfully integrate the IoT sensing network, edge-cloud computing infrastructure, hybrid LSTM-XGBoost predictive load forecasting model, and adaptive control via model predictive control.

The main results were as follows:

- High-Fidelity IoT Monitoring is Feasible: The use of 200 low-cost smart energy monitoring devices and edge gateways turned out to be an effective method of collecting detailed and timely data (with 1-second resolution) from the low voltage network.
- Hybrid AI Model Greatly Enhances Predictions: The implementation of the hybrid LSTM-XGBoost model by using both temporal learning of LSTMs and feature interactions of XGBoost resulted in extremely high prediction accuracy (96.2% R^2), which is critical for further controller performance.
- The Proposed MPC Method Can Shape Loads Effectively: The proposed MPC-based control scheme managed to shave peak load demand by 27.4%, as well as lower energy expenditure by 19.8%, demonstrating superiority over traditional TOU schemes. Furthermore, this control strategy was able to strike an appropriate balance between grid stability and comfort of users, ensuring that the former did not exceed a threshold of <1.5 min/d violations.
- The Control Strategy Is Real-Time Compatible: With a computation time of 0.87 sec on average over 6 hr horizons, the developed controller is capable of responding to unforeseen changes in grid performance, including drops in renewable generation, and avoiding grid overloading.

This research provides several important implications for grid system operators. First of all, by using this control mechanism, the latter will be able to avoid expensive grid renovations and maximize existing capacity utilization. Secondly, they will be able to minimize expenses related to the maintenance of grids, reducing their peak load.

Although the outcomes have been very encouraging, there are limitations to the study. For example, the experiment was performed in only one suburban location, and thus, the urban or industrial grids were not well captured by the results. In addition, the consumer comfort model was relatively simplistic and did not consider all possible consumer preferences. Future studies will include the expansion of the testbeds to 2,000 households in various demographic areas. Moreover, future studies will include electric vehicle chargers as extremely flexible loads and the design of a more advanced consumer preference learning model through reinforcement learning.

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