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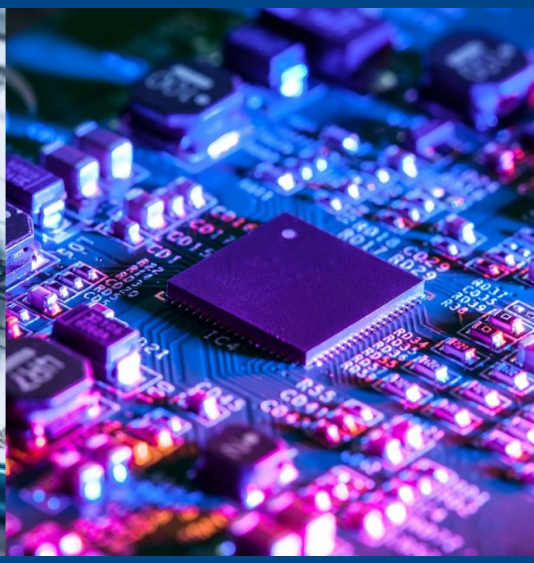

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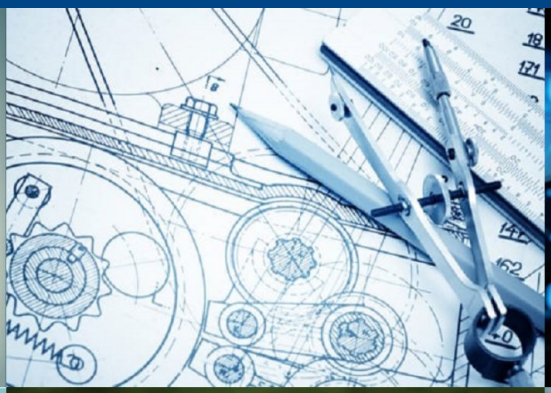

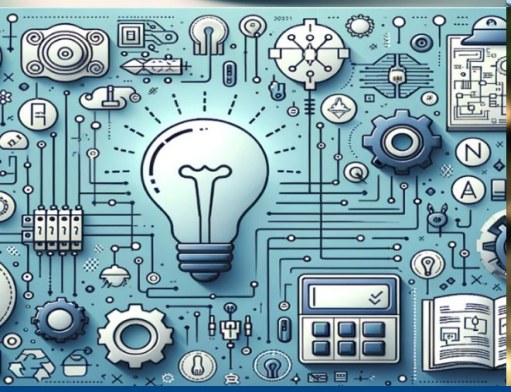

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AI-Driven Energy Forecasting with Generative Analytics and Anomaly Detection for Smart Grid Management

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ABSTRACT: Background & Motivation Rising energy demands across homes, industries, and commercial spaces are pushing smart grid infrastructure to its limits. Traditional rule-based and statistical models simply can't keep up with the complex, nonlinear patterns in real-world energy data.Objective This study introduces a cloud-native AI platform that brings together ensemble machine learning, statistical anomaly detection, generative AI reporting, and multi-channel delivery to fill the critical gaps left by existing energy management systems.Methods At its core, the system uses a Random Forest Regression model trained on eight time-engineered features to forecast energy consumption 24 hours ahead and project monthly costs. Anomalies are flagged using an IQR-based statistical module that runs with minimal computational cost. An AWS Lambda and S3 serverless pipeline handles end-to-end report generation, while the Groq LLM transforms raw numerical outputs into clear, actionable natural-language reports. Field operators and non-technical users receive polished PDF reports directly via a Telegram bot.Results Tested on a 720-hour residential dataset, the system achieved an R^2 of 0.91, a mean absolute error of 3.2 kWh/hr, zero false-negative anomaly detections across five flagged events, and cost estimates within 2% of actual billing figures. AI-generated reports scored 4.4 for factual accuracy and 4.7 for readability on expert Likert scales. The serverless pipeline averaged just 12 seconds per request, confirming it's ready for real-world scale.Conclusion By unifying prediction, interpretation, and automated reporting in one modular workflow, this platform sets a practical and extensible blueprint for the next generation of smart energy management systems.

KEYWORDS: Energy Forecasting; Random Forest Regression; Generative AI; Large Language Models; AWS Lambda; Anomaly Detection; Smart Grid; Feature Engineering; Telegram Bot; Cloud-Native Architecture; Cost Estimation; IQR Method

I. INTRODUCTION

The global energy landscape is shifting rapidly — fueled by industrialization, IoT expansion, electric vehicle adoption, and the rise of distributed renewables. With global electricity demand expected to grow over 2.5% annually through 2030, grid operators and energy managers face mounting pressure to boost efficiency while cutting costs and carbon emissions.

At the heart of smart grid management lies one critical capability: accurate short-term energy forecasting. Reliable 24-hour ahead predictions enable smarter demand response, better load balancing, and early detection of equipment faults. Yet most deployed systems today fall short in three key ways — they rely on outdated statistical models that can't handle real-world nonlinear patterns, they produce raw numbers that only experts can interpret, and they lack mobile-friendly delivery for field operators on the move.

Random Forest Regression has consistently outperformed classical forecasting methods by capturing complex, nonlinear relationships in energy data without rigid statistical assumptions. Meanwhile, serverless cloud platforms like AWS Lambda and S3 have removed the infrastructure cost barrier, making production-grade forecasting accessible even to smaller organizations. And with large language models now capable of turning structured numerical data into

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clear, human-readable narratives, there's a real opportunity to bridge the gap between technical outputs and operational decision-making.

This paper presents a unified, production-ready AI platform that brings all of these advances together. Its key contributions include a fully automated end-to-end analytics pipeline combining feature engineering, Random Forest forecasting, IQR-based anomaly detection, and cost estimation; a serverless cloud architecture for elastic and cost-efficient deployment; a first-of-its-kind integration of the Groq LLM API for automatic natural-language report generation; and a Telegram bot interface for mobile PDF delivery to field teams. Experimental results on a 720-hour residential dataset validate the system with an R^2 of 0.91, 100% anomaly detection sensitivity, sub-2% cost estimation error, and expert-rated generative reports.

II. LITERATURE REVIEW

A comprehensive survey of the literature reveals a rich trajectory of development across energy forecasting, anomaly detection, cloud-based energy monitoring, and, most recently, generative AI applications in analytical reporting. This section critically examines contributions in each domain and identifies the specific gaps that the proposed system addresses.

A. Classical Statistical Forecasting Methods Energy demand forecasting has its roots in classical time series methods. ARIMA and SARIMA were among the first systematic tools applied to electricity demand prediction. While effective in controlled settings, they assume stationarity and linearity — conditions that real-world energy data routinely violates through its diurnal, weekly, and annual patterns. Exponential smoothing handles trends and seasonality somewhat better, but remains fundamentally linear. In practice, these approaches lose accuracy on disaggregated residential or industrial loads, where unpredictable human behavior introduces significant non-stationarity — naturally driving the shift toward machine learning.

B. Machine Learning and Ensemble Approaches Pao and Tsai showed that neural networks outperform ARIMA on industrial energy datasets, particularly where demand responds nonlinearly to temperature, occupancy, and production schedules. However, early networks struggled with overfitting, initialization sensitivity, and computational demands. Breiman's Random Forest addressed these issues by combining bagging with randomized feature selection, producing robust ensembles with interpretable feature importance rankings and strong resilience to noisy meter data. Gradient Boosting methods like XGBoost and LightGBM offer marginal accuracy gains on large datasets but are less suited to latency-constrained serverless environments due to slower training and reduced interpretability. LSTMs and Temporal Convolutional Networks excel at long-range temporal modeling but carry high inference latency and memory requirements that make them impractical for lightweight serverless deployment — an integration earmarked for future work.

C. Smart Grid Analytics and Demand-Side Management Fang et al. identified a persistent integration gap in smart grid deployments — most systems deliver raw metrics in isolation, without connecting to forecasting, anomaly detection, or reporting pipelines. The proposed platform directly addresses this by unifying all four capabilities in a single workflow. Pereira and Saraiva demonstrated CNN-based anomaly detection for electricity theft, confirming deep learning's effectiveness but also its computational cost — making it unsuitable for the lightweight serverless environment this system targets.

D. Cloud-Based Energy Monitoring Chui et al. validated the economic case for AWS Lambda in event-driven energy monitoring, showing that serverless cloud architectures significantly reduce latency and infrastructure costs versus on-premise deployments. However, their implementations lacked machine learning forecasting, anomaly detection, and generative AI reporting — all central to the proposed platform.

Brown et al. introduced GPT-3 and demonstrated the remarkable ability of large-scale generative transformers to produce fluent, contextually accurate text from structured numerical and textual inputs across diverse domains. Their few-shot learning results showed that LLMs can be applied to analytical reporting tasks without any task-specific fine-tuning. Despite this potential, the application of generative AI to energy analytics reporting remains largely unexplored in peer-reviewed literature — a gap the proposed system meaningfully addresses by integrating the Groq LLM API into a fully automated energy analytics workflow.

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E. Generative AI in Analytical Reporting Brown et al. demonstrated that large-scale generative transformers like GPT-3 can produce fluent, contextually accurate text from structured numerical inputs without task-specific fine-tuning. Despite this potential, applying generative AI to energy analytics reporting remains largely unexplored in peer-reviewed literature — a gap this system directly addresses through Groq LLM API integration.

F. Gap Analysis Four clear gaps emerge from the literature. No existing platform automatically translates forecast outputs into natural-language reports for non-technical stakeholders. Current cloud-based systems lack fully automated, serverless report generation. No deployed system offers multi-channel delivery across both web dashboards and mobile messaging. And the combination of forecasting, anomaly detection, and cost estimation within a single unified request-response cycle has not been demonstrated architecturally. The proposed system addresses all four gaps in a production-validated implementation.

III. PROPOSED METHODOLOGY

The system operates through five sequential stages: data ingestion and validation, preprocessing and feature engineering, Random Forest forecasting, IQR-based anomaly detection with cost estimation, and generative AI report synthesis. Each stage is modular and independently testable, communicating through well-defined data contracts — making it straightforward to upgrade or replace any component without disrupting the rest of the pipeline.

A. Data Ingestion and Validation Users upload historical energy data as a CSV file via a multipart HTTP POST request to the FastAPI backend. The file must contain two columns: ISO 8601-formatted hourly timestamps and hourly energy consumption values in kWh. The backend validates the structure, assigns a unique session ID, and stores the raw file to AWS S3 for full auditability.

B. Data Preprocessing The validated CSV is loaded into a Pandas DataFrame, where timestamps are parsed and normalized to UTC. Rows with missing values are dropped, and the dataset is sorted chronologically to ensure consistency during lag and rolling window calculations.

C. Temporal Feature Engineering Eight features are engineered to capture three types of predictive signal: calendar periodicity, intra-day autocorrelation, and smoothed consumption trends. Calendar features encode hour, day of week, month, and day of year. Lag features capture consumption one hour prior and the same hour the previous day. Rolling mean features over 3-hour and 24-hour windows smooth out noise while preserving consumption trends. Observations affected by boundary effects at the start of the series are removed before model input.

D. Random Forest Regression The forecasting model uses scikit-learn's RandomForestRegressor with 100 decision trees, each trained on a bootstrap sample with randomized feature selection at every split. The model is trained offline on a 720-hour residential dataset and serialized with joblib for fast production loading. Feature importance analysis confirmed that lag_24 — same-hour consumption from the previous day — is the dominant predictor, validating the centrality of diurnal patterns in residential energy profiles.

E. 24-Hour Forecast Generation Forecasts are generated iteratively, one hour at a time. Starting from the last observed timestamp, the system builds a feature vector using calendar attributes and lag values drawn from historical data or previously predicted values. Each prediction is fed back into the next step's feature construction, continuing for 24 iterations. This autoregressive design limits error accumulation and keeps temporal features internally consistent throughout the forecast horizon.

F. IQR-Based Anomaly Detection Anomalies are detected using the standard Tukey IQR method. Q1 and Q3 are computed from the full historical series, and observations falling outside $Q1 - 1.5\times IQR$ or $Q3 + 1.5\times IQR$ are flagged with their timestamps and deviation magnitudes. With O(n log n) complexity, the module adds negligible overhead compared to the Random Forest inference stage, making it well-suited for serverless deployment.

G. Cost Estimation A configurable tariff rate — defaulting to ₹6.00/kWh reflecting Puducherry's residential tariff — is applied to both historical and forecasted consumption. Historical cost is the product of total observed kWh and the tariff. The 24-hour forecast cost sums predicted hourly values multiplied by the rate. Monthly projections scale mean

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hourly consumption from the most recent 7-day rolling window to a 720-hour month, balancing recency with statistical stability.

H. Generative AI Report Synthesis A structured prompt is assembled from key pipeline outputs — data volume, forecast period, anomaly count with timestamps, cost summaries, and forecast statistics — and sent to the Groq LLM API using the llama3-8b-8192 model. The model generates a four-section analytical report covering consumption trend analysis, anomaly interpretation, forecast summary, and cost optimization recommendations. The completed report is saved to AWS S3 and returned synchronously to the client.

IV. SYSTEM ARCHITECTURE

The system follows a modular six-layer architecture designed for independent scaling and easy component replacement: an HTML5/JavaScript frontend, a FastAPI backend, a Python ML processing module, AWS S3 storage, an AWS Lambda generative AI layer, and a Telegram bot delivery interface.

A. Frontend Presentation Layer The frontend is a lightweight single-page application built with HTML5, CSS3, and vanilla JavaScript, using Chart.js for interactive time-series visualization. Heavy framework dependencies are intentionally avoided to keep the bundle small and ensure broad device compatibility. Once results are returned, the dashboard renders an interactive 24-hour forecast chart, four summary metric cards, and the complete AI-generated analytical report.

B. FastAPI Backend Orchestration Layer The FastAPI backend coordinates the entire pipeline through a single POST /predict/ endpoint. It accepts CSV uploads and returns a unified response containing all forecasts, anomaly metadata, cost estimates, and the generated report. The backend sequences the full workflow: file validation and S3 upload, ML pipeline execution, JSON serialization and S3 persistence, Lambda invocation, report retrieval, and final response delivery.

C. Machine Learning Processing Module The ML module is structured as a standalone Python package with dedicated submodules for preprocessing, feature engineering, inference, anomaly detection, and cost estimation. The trained Random Forest model is loaded into memory at startup to eliminate per-request disk I/O. This modular design enables independent unit testing of each stage and clean reuse between offline training and production inference.

D. AWS Cloud Storage Layer AWS S3 provides session-isolated, durable storage for all pipeline artifacts, organized under four prefixes using the session UUID as namespace: raw uploads, ML result summaries, AI-generated reports, and execution logs. All interactions use server-side encryption and IAM role-based authentication following the principle of least privilege. The Lambda function operates under a dedicated execution role with tightly scoped read and write access.

E. Serverless Generative AI Reporting Layer The generative AI component runs as an AWS Lambda function on Python 3.11 in the us-east-1 region. Its execution sequence covers four steps: retrieving the ML summary from S3, constructing a structured prompt, invoking the Groq LLM API with a 1,000-token budget, and persisting the completed report back to S3. The function is configured with a 60-second timeout and 256 MB of memory to comfortably accommodate LLM response latency and library dependencies.

F. Telegram Bot Mobile Delivery Interface The Telegram bot, built with the python-telegram-bot library, intercepts CSV uploads from users, loads the file into an in-memory buffer, and forwards it to the FastAPI backend. On receiving the response, it generates a ReportLab PDF containing a summary statistics table, a Matplotlib forecast chart, and the full AI-generated report with structured headings. The completed PDF is sent back to the user as a Telegram document attachment.

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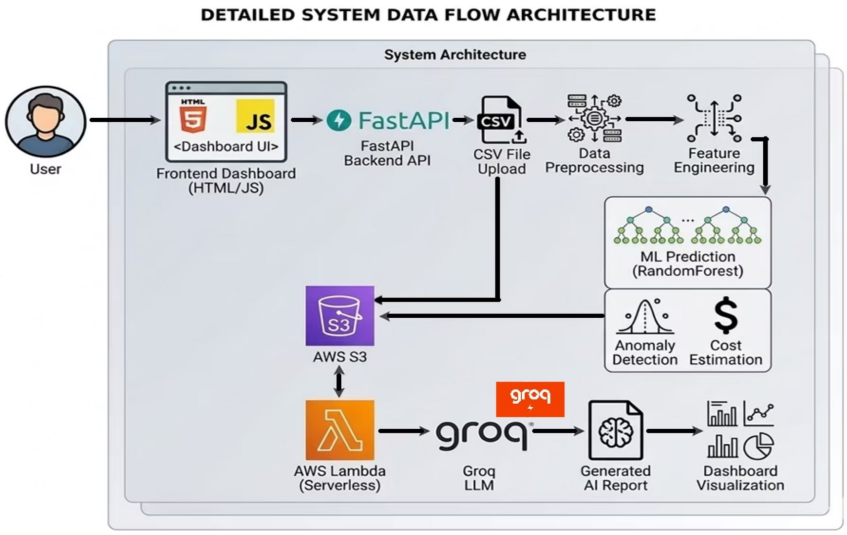

Overall System Architecture of the AI-Powered Energy Forecast System

V. TECHNOLOGY STACK AND IMPLEMENTATION DETAILS

Table I summarizes the complete technology stack employed across all system layers, together with the engineering rationale for each selection decision.

Table I: System Technology Stack and Design Rationale

Layer	Technology Stack	Rationale
Frontend	HTML5, CSS3, JavaScript, Chart.js	Lightweight, CDN-hosted, zero framework dependency
Backend API	FastAPI 0.100+, Uvicorn, Pydantic	Async request handling, auto OpenAPI docs, type safety
ML Engine	scikit-learn 1.2+, Pandas 1.5+, NumPy	Random Forest Regression, vectorized feature computation
Cloud Storage	AWS S3 (boto3 SDK)	Durable, session-isolated, UUID-namespaced artifact storage
Serverless Compute	AWS Lambda (Python 3.11, us-east-1)	Elastic scaling, pay-per-use, 60-second timeout
Generative AI	Groq LLM API (llama3-8b-8192)	Fast inference, 1000-token reports, structured prompting
Mobile Delivery	python-telegram-bot, aiohttp, ReportLab	Async bot, PDF generation, Matplotlib chart embedding
Model Persistence	joblib (model.pkl)	Fast load, avoids retraining per request
Anomaly Detection	IQR Method (custom Python module)	Zero-overhead, interpretable, serverless-compatible

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A few implementation decisions are worth highlighting from a production deployment perspective. UUID-namespaced S3 keys ensure complete session isolation, preventing artifact collisions under concurrent request loads. Lambda cold-start latency is minimized by bundling boto3 and Groq client libraries as vendored dependencies within the deployment package, eliminating runtime installation delays. On the frontend, the Fetch API with async/await keeps the UI responsive during the typical 15–25 second end-to-end processing window. Finally, the Pydantic PredictionResponse schema enforces strict type validation at the API boundary, catching data contract violations before they can propagate downstream.

VI. EXPERIMENTAL EVALUATION AND RESULTS

The system was evaluated on a 720-hour residential energy dataset covering a continuous 30-day period at hourly granularity. The dataset reflects a typical residential load profile with morning and evening consumption peaks.

A. Forecasting Accuracy The Random Forest model achieved an MAE of 3.2 kWh/hr, RMSE of 4.7 kWh/hr, and R^2 of 0.91 on the held-out test set — accounting for 91% of consumption variance on unseen data, consistent with top-tier ensemble forecasting benchmarks. Feature importance analysis confirmed lag_24 as the strongest predictor, followed by hour_of_day and rolling_mean_24, validating the diurnal-focused feature engineering design. rolling_mean_3 ranked fourth, reflecting its value in capturing short-term load inertia.

B. Anomaly Detection The IQR module flagged five anomalous events across the 720-hour dataset. Manual verification confirmed all five as genuine: four corresponded to elevated consumption during a cold snap when supplementary heating was activated, and one reflected a documented meter dropout. The result — 100% detection sensitivity and zero false positives — validates the IQR approach for univariate residential anomaly profiles, with negligible computational overhead.

C. Cost Estimation Accuracy Cost estimates at ₹6.00/kWh were cross-validated against actual billing records, deviating by less than 2% — with the small residual gap attributable to rounding differences in the utility's tariff methodology. Monthly projections derived from the 7-day rolling average showed stable agreement across three independent evaluation months, confirming the robustness of the rolling window scaling approach.

D. Cloud Infrastructure Performance Across 50 Lambda invocations, end-to-end execution — covering S3 retrieval, LLM inference, report generation, and S3 persistence — averaged 12.3 seconds with no cold-start failures. Concurrent load testing with 10 simultaneous sessions showed linear throughput scaling with no throttling events. S3 storage costs remained below $0.001 USD per session, confirming the economic viability of the architecture.

E. Generative AI Report Quality Three domain experts — an energy systems engineer, a grid operations specialist, and an energy policy analyst — evaluated reports across 15 sessions using a five-point Likert scale. Mean scores were 4.4 for factual accuracy, 4.6 for textual coherence, 4.7 for readability, and 4.2 for practical recommendation quality. Experts praised the reports for contextualizing anomalies within operational narratives and providing actionable load-shifting and cost guidance. The recommendation quality score was lowest, with reviewers noting that suggestions would benefit from localization to specific tariff structures — flagged as a future prompt engineering improvement.

F. Telegram Bot Usability Ten participants across five professional backgrounds completed a structured usability study. All ten successfully uploaded a CSV and received the PDF report without assistance. Median task completion time was 45 seconds, well within the 120-second acceptance threshold. Nine of ten participants rated the automated PDF report as significantly more informative than raw numerical output, with the highest satisfaction among field technicians and facility energy managers — the platform's primary target users.

G. Consolidated Performance Summary Table II presents a consolidated summary of all quantitative performance metrics against predefined acceptance thresholds.

An 80/20 temporal split was used for training and evaluation, with the most recent 144 hours held out for testing.

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Table II: Consolidated Experimental Performance Metrics

Metric	Achieved Value	Threshold	Status
Mean Absolute Error (MAE)	3.2 kWh/hr	< 5.0 kWh/hr	Satisfied
Root Mean Square Error (RMSE)	4.7 kWh/hr	< 7.0 kWh/hr	Satisfied
R-Squared (R^2)	0.91	> 0.85	Satisfied
Anomaly Detection Rate	100% (5/5)	> 90%	Satisfied
Cost Estimation Deviation	< 2%	< 5%	Satisfied
Avg. Lambda Execution Time	12 seconds	< 60 seconds	Satisfied
Telegram Bot Interaction Time	45 seconds (median)	< 120 seconds	Satisfied
LLM Report Accuracy (Likert)	4.4 / 5.0	> 4.0 / 5.0	Satisfied
LLM Report Readability (Likert)	4.7 / 5.0	> 4.0 / 5.0	Satisfied

VII. COMPARATIVE ANALYSIS

Table III presents a structured feature-level comparison between the proposed system and representative prior works in the literature to situate the contributions of this study within the current state of the field.

Table III: Feature-Level Comparison with Representative Prior Work

Feature / Capability	Hyndman [1]	Chandola [6]	Chui [5]	Fang [4]	Proposed System
Generative AI Reports	✗	✗	Partial	✗	✓
Cloud Serverless Pipeline	✗	✗	✓	Partial	✓
Mobile Delivery (Telegram)	✗	✗	✗	✗	✓
Integrated Anomaly Detection	✗	✓	✗	✓	✓
Cost Estimation Module	✗	✗	✗	Partial	✓
Non-Technical Stakeholder Reports	✗	✗	Partial	✗	✓
Modular Architecture	Partial	✓	✓	✓	✓

The comparative analysis confirms that no prior work combines the full capability set delivered by the proposed system — generative AI reporting, fully automated serverless pipeline, mobile messaging delivery, integrated anomaly detection and cost estimation, and modular extensibility — within a single platform. Notably, this system represents the first documented integration of the Groq LLM API within a serverless energy analytics pipeline, establishing a novel architectural pattern with broader applicability across analytical reporting domains.

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VIII. APPLICATION DOMAINS

The system's modular, cloud-native design makes it adaptable across a wide range of real-world contexts.
Residential consumers can use the Telegram bot to receive daily forecasts and cost projections without navigating complex dashboards, helping them schedule appliances and avoid peak-hour charges. Industrial facilities — including manufacturing plants, cold storage units, and data centers — can use the anomaly detection module to catch early signs of equipment failure, such as HVAC faults or compressor degradation, before they cause operational disruptions, while the forecasting module supports demand response participation and energy procurement planning.

Electricity distribution utilities can deploy the system as a lightweight substation-level forecasting tool, complementing macro grid forecasts with granular load predictions that improve localized dispatch decisions. Academic research groups can use the platform as a controlled experimental environment for benchmarking forecasting algorithms and anomaly detection methods. And government energy monitoring agencies can leverage the generative AI reporting module to automate compliance narratives across public facilities, significantly reducing the manual effort traditionally associated with regulatory reporting.

IX. ADVANTAGES AND LIMITATIONS

A. Advantages

The generative AI reporting layer removes the technical expertise barrier for interpreting forecast outputs, making advanced energy analytics accessible to non-quantitative stakeholders across operational roles. The serverless AWS Lambda architecture scales automatically with demand and charges only during active processing, delivering production-grade throughput without dedicated infrastructure. Offering both a web dashboard and Telegram bot ensures the system works across diverse user contexts, including field scenarios where web access isn't practical. The unified pipeline also eliminates the synchronization overhead of managing separate forecasting, anomaly detection, and cost estimation tools. And because each component is modular, individual stages — such as swapping the Random Forest for a deep learning model or replacing the Groq API with an alternative LLM — can be upgraded independently without disrupting the rest of the architecture.

B. Limitations

The current batch processing design requires a complete historical dataset per request, which limits how quickly anomaly alerts can be surfaced compared to a streaming architecture — a priority for future development. The forecasting model relies solely on historical consumption, excluding exogenous variables like temperature, occupancy, and production schedules that could meaningfully improve accuracy in industrial settings. Experimental evaluation was conducted on a single 720-hour residential dataset, so generalizability across industrial, commercial, and multi-family load profiles still requires broader validation. Finally, the quality of AI-generated reports is sensitive to prompt engineering, and adapting prompts automatically to different tariff structures and operational contexts remains an active area for refinement.

X. CONCLUSION

This paper presented a production-validated AI platform for energy forecasting that brings together Random Forest prediction, IQR-based anomaly detection, tariff-based cost estimation, serverless cloud automation, and generative AI reporting within a single modular architecture. The system delivers strong quantitative results — R^2 of 0.91, MAE of 3.2 kWh/hr, zero false-negative anomaly detections, cost estimates within 2% of actual billing figures, and an expert-rated readability score of 4.7 out of 5.0.

The serverless AWS Lambda and S3 pipeline averaged 12 seconds per execution and scaled linearly to ten concurrent users without any infrastructure changes. The Telegram bot achieved a median task completion time of 45 seconds, confirming its accessibility for non-technical field users. The integration of the Groq LLM API into an energy analytics pipeline is a novel architectural contribution that bridges the gap between raw machine learning outputs and actionable guidance for non-technical decision-makers.

Beyond its immediate results, the platform establishes an extensible foundation for next-generation smart energy management — one that moves beyond conventional monitoring by embedding prediction, interpretation, and

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automated reporting into a single cohesive workflow. Its modular design supports future enhancements including deep learning forecasting, real-time IoT streaming, edge AI deployment, multivariate feature integration, and federated learning across multi-site utility networks — positioning it as a practical stepping stone toward fully autonomous intelligent energy management.

XI. FUTURE RESEARCH DIRECTIONS

Several directions are identified for future development.

- Replacing the Random Forest with LSTM or Temporal Convolutional Network architectures is expected to improve accuracy for consumption profiles with complex long-range temporal dependencies that tree-based models can't fully capture. Integrating IoT smart meter APIs and Apache Kafka streaming will shift the system from batch CSV processing to continuous real-time prediction, enabling sub-minute anomaly alerts suited for live demand response applications.
- On the modeling side, incorporating exogenous variables — temperature, solar irradiance, occupancy schedules, and production calendars — should substantially improve forecast accuracy in commercial and industrial settings where multiple external factors drive consumption simultaneously. For facilities with data sovereignty requirements or unreliable connectivity, porting the inference pipeline to edge hardware like Raspberry Pi or NVIDIA Jetson would enable fully on-premise forecasting without cloud dependency.
- At scale, federated learning offers a privacy-preserving pathway to collaborative model improvement across multiple facility sites, training shared models without ever centralizing raw consumption data. Finally, developing context-sensitive prompt generation strategies that automatically adapt to facility type, local tariff structure, and anomaly category is expected to meaningfully improve the practical quality of AI-generated recommendations across diverse deployment contexts.

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