Machine-Learning-Driven Framework for Industrial Energy Monitoring

Pavan Reddy S
Dept. of ECE
Dayananda Sagar University
Karnataka, India
Pavanreddy.s9242@gmail.com

Pramodh RS
Dept. of ECE
Dayananda Sagar University
Karnataka, India
rspramodh5@gmail.com

Rakshak K R
Dept. of ECE
Dayananda Sagar University
Karnataka, India
krrakshak12@gmail.com

Kirthann R
Dept. of ECE
Dayananda Sagar University
Karnataka, India
kirthan60@gmail.com

Godfrey D
Dept. of ECE
Dayananda Sagar University
Karnataka, India
godfrey1707@gmail.com
*Corresponding author

Abstract— Real-time energy monitoring and predictive analytics are essential for industrial efficiency. This paper presents an IoT-based system integrating an STM32F446RE microcontroller, Modbus RTU, and BE33 Bluetooth for data acquisition. The Rugged Board A5D2x serves as an edge gateway, transmitting data to the cloud for advanced analytics. The system enables anomaly detection, predictive billing, and historical trend evaluation. Results show a slight overestimation of anomalies (52.94% predicted vs. 47.06% actual), ensuring robust detection. Frequency anomalies are conservatively detected (0.28% predicted vs. 0.14% actual), while current, RMP, and power anomalies align closely with actual values. Energy consumption remains stable with no anomalies. Predictive billing analysis estimates industrial costs across tariffs ranging from ₹6.72/kWh to ₹9.56/kWh, optimizing financial planning. The cloud-based architecture enhances scalability and accessibility, improving energy management strategies.

Keywords—Energy monitoring, IoT, Anomaly detection, Predictive analysis, Cloud computing.

I. Introduction

Industries are increasingly adopting smart energy monitoring systems to enhance efficiency, reduce costs, and optimize power consumption. Traditional energy management systems often lack real-time insights and predictive capabilities, making them less effective for industrial applications [1]. Advanced sensing, data collection, and cloud analytics are all integrated into contemporary Industrial IoT(IIoT) based solutions to facilitate intelligent decision-making and real-time monitoring [2].

In order to facilitate real-time energy monitoring, anomaly detection, and predictive billing analysis, we present an Advanced Industrial Energy Monitoring System in this work that combines the STM32F446RE microcontroller, Modbus RTU protocol, Bluetooth-based rugged board communication, and ThingsBoard cloud integration. The STM32 microcontroller was chosen because it is perfect for IIoT-based energy monitoring systems due to its low power consumption, real-time processing capabilities, and interoperability with industrial protocols [3]. Industrial settings have experimented with embedded system-based monitoring solutions, like ZigBee, but they frequently have latency and scalability issues [4]. For reliable data transfer between the energy meter and STM32, our system makes use of Modbus RTU, guaranteeing effective communication in industrial settings [5]. Modbus was chosen because of its broad use in industrial automation, ease of implementation, and dependability [6]. Complex cable configurations are no longer necessary thanks to Bluetooth connectivity between the STM32 and a rugged board, which allows wireless data exchange [7].

After that, the rugged board sends telemetry data to the ThingsBoard cloud platform, which offers an intuitive user interface for analytics and real-time visualization [8]. Our system's machine learning-based anomaly detection is a crucial component. Deep learning-based anomaly detection algorithms can be used to identify abnormalities in industrial energy consumption patterns that are frequently caused by malfunctioning machinery, power spikes, or inefficiency [9].

Unlike traditional methods that rely on rule-based threshold detection, our system guarantees higher accuracy and adaptability to dynamic industrial conditions [10], and our predictive billing analysis module estimates energy costs using dynamic tariff structures, helping industries optimize energy usage and reduce expenses [12]. In addition, fine-grained energy measurements and machine learning models improve the accuracy of predictive billing, enabling industries to forecast energy costs and take proactive measures [13]. While real-time data visualization is provided by existing approaches, such as ESP32-based monitoring systems, they lack predictive analytics and industrial scalability [14].

ThingsBoard is a top open-source IoT platform for industrial applications, and we use it to guarantee smooth cloud-based visualization and monitoring. ThingsBoard is a great option for energy monitoring solutions because it allows for event-triggered alerts, historical data analysis, and configurable dashboards [15]. Our method is very effective for industrial-scale energy management because it combines cloud analytics, machine learning, and embedded technologies. Our technology takes into account energy prices and billing trends in addition to monitoring and anomaly detection. Different industries and geographical areas have different energy tariff systems, which have a big influence on operating expenses. The need for dynamic billing models that take into consideration peak demand charges, seasonal variations, and governmental regulations is highlighted by studies on tariff setting in the Indian power sector [16]. In order to ensure efficient power usage and cost savings, smart energy meters with automatic tariff controllers have been proposed for industrial applications [17]. Data-driven energy management techniques are crucial for reducing costs and increasing efficiency, according to a comparative study of electricity rates in India [18]. NITI Aayog reports emphasize the importance of intelligent power monitoring in optimizing tariff-based invoicing and minimizing industrial energy waste [19].

II. IEMS Framework and Implementation

Real-time analytics and effective energy monitoring are made possible by the integration of essential hardware and software components in the Industrial Energy Monitoring System (IEMS). Using a rugged board (AD2x), Bluetooth (BE33), Modbus RTU, and an STM32F446RE microcontroller, the system is made to guarantee smooth data capture, transfer, and processing. In addition to processing sensor data, the STM32F446RE microcontroller facilitates communication between different parts of the system. In order to ensure precise and dependable data collection for anomaly detection and predictive analysis, it uses Modbus RTU to obtain energy consumption data from industrial energy meters [6]. Bluetooth (BE33) is utilized to connect the rugged board (AD2x) and the STM32 microcontroller in order to provide wireless data transfer. After processing the collected data, the rugged board sends telemetry data to the cloud for analytics and real-time monitoring. In industrial settings, this architecture improves flexibility and scalability by doing away with the requirement for intricate wiring connections. The testbed architecture created for this study is depicted in Fig. 1, which also shows how hardware components are integrated and data flows across the system.

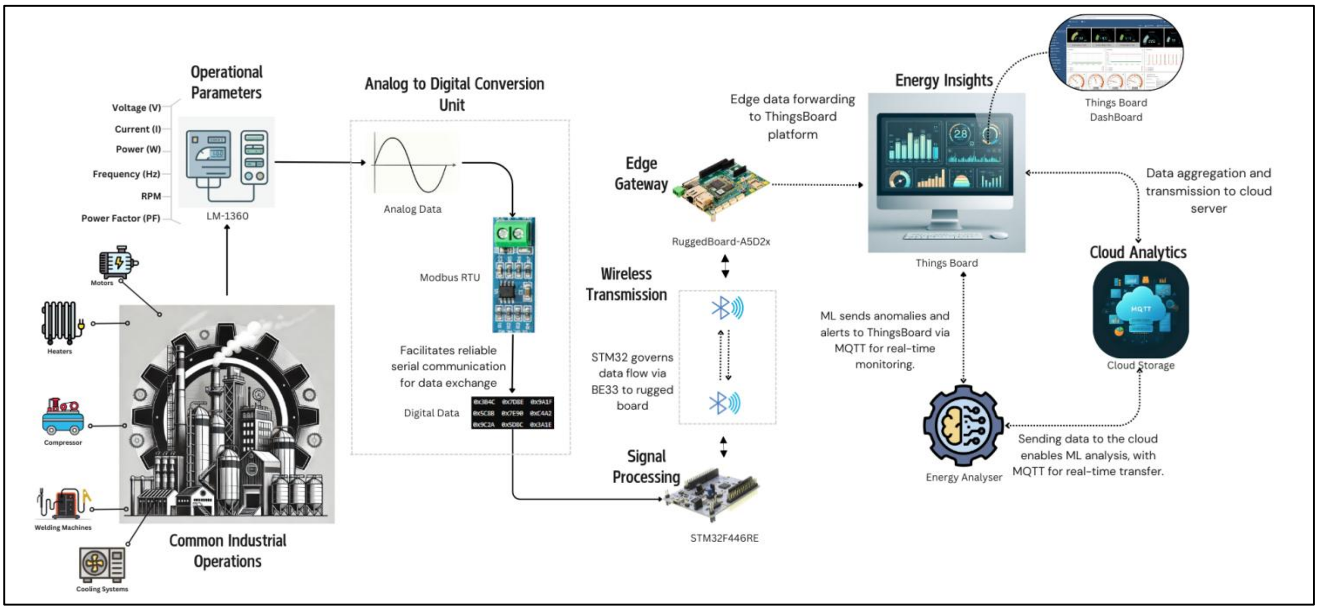

Fig. 1: The Operational flow diagram of the testbed built for this research

The Advanced Industrial Energy Monitoring System combines essential elements to guarantee effective cloud storage, processing, and data collecting. Our research work addresses issues such as system robustness, processing efficiency, and wireless data transmission dependability in order to optimize energy data collecting and real-time monitoring for industrial settings. This entails optimizing transmission procedures, strengthening system reactivity to anomalies, and honing data validation approaches for smooth industrial energy management. In order to ensure fault tolerance and smooth data transfer, Fig. 2 shows the data flow in our system, showing how sensor readings move from industrial loads to cloud storage.

Modbus RTU, which was selected for its precision and resilience in challenging conditions, is the primary means by which the STM32F446RE microcontroller collects real-time data from industrial energy meters. In order to lower computational overhead and improve processing performance, the microcontroller organizes data in hexadecimal format and conducts single-channel ADC conversion. We integrate the BE33 Bluetooth module, creating a direct link between STM32 and the Rugged Board (RB A5D2x) for wireless transmission. Bluetooth is preferred over Wi-Fi for its low power consumption, minimal interference, and ease of industrial integration. However, to address potential transmission failures, we implement a data retransmission mechanism that ensures reliability and minimizes packet loss.

The workflow of our anomaly detection and predictive bill analysis system, shown in Fig. 3, ensures efficient industrial energy monitoring. Real-time telemetry data is collected via MODBUS RTU between the energy meter and STM32. The raw data undergoes preprocessing, including cleaning and normalization, to maintain consistency. Relevant features are then extracted for analysis. Using TensorFlow, the anomaly detection module applies auto encoders and isolation forests to identify deviations in energy usage. Detected anomalies trigger real-time alerts on ThingsBoard Cloud, enhancing monitoring and system response. Simultaneously, the predictive bill analysis module processes the same telemetry data to estimate future energy costs. The model incorporates unit price references from BESCOM and historical consumption data to forecast electricity bills.

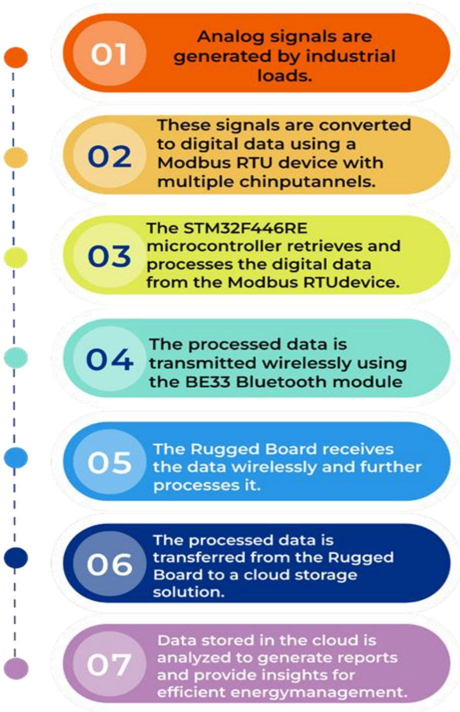

Fig. 2: Data Flow Diagram for IEMS

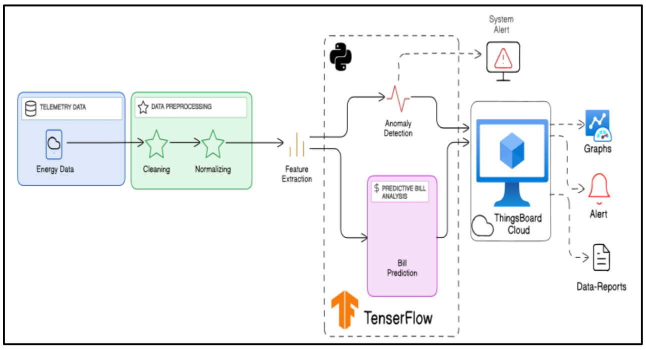

Fig. 3: Machine Learning Workflow

While the current implementation uses static tariff references, the future plan is to integrate with BESCOM's REST API for real-time tariff updates, ensuring dynamic and accurate cost predictions. The system generates graphs, alerts, and data reports, aiding in energy optimization and cost management.

The anomaly detection system processes telemetry data to identify deviations in energy consumption. With an accuracy of 0.99, the model effectively classifies normal and anomalous data points, though dataset imbalance impacts recall, which remains low at 0.11, indicating undetected anomalies. A precision of 0.89 ensures most identified anomalies are accurate, minimizing false positives. However, the F1-score of 0.20 highlights the need for improvement. Refining feature selection, optimizing detection thresholds, and integrating adaptive learning will enhance detection performance, ensuring robust real-time monitoring. Fig. 4 – Comparative Analysis of Performance Metrics illustrates these results.

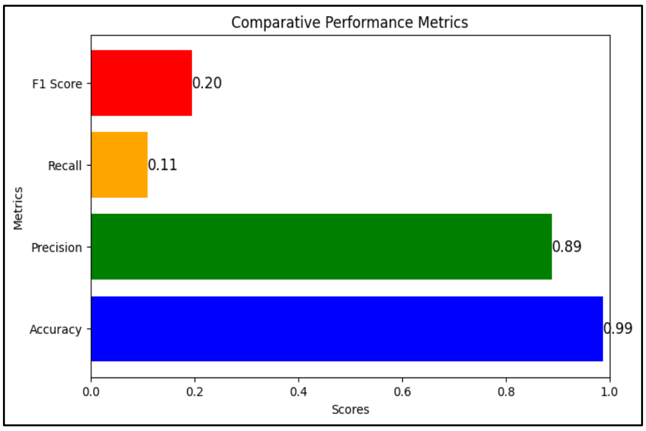

Fig 4 - Comparative Analysis of Performance Metrics

III. Results and Analysis

A. ThingsBoard Dashboard for Real-Time Energy Monitoring

The ThingsBoard IoT platform supplies the Graphical User Interface (GUI) production ready server facility to connect your smart meter devices, collect, transfer, store and analyze smart metering data through online, and share results of the analysis with the real time-users. The Fig.5 provides a live visualization of key energy parameters, enabling real-time tracking and analysis of consumption patterns for efficient monitoring and anomaly detection. The Graphical user Interface in the ThingsBoard platform has Current, Power, Voltage, Energy, Power factor and RPM.

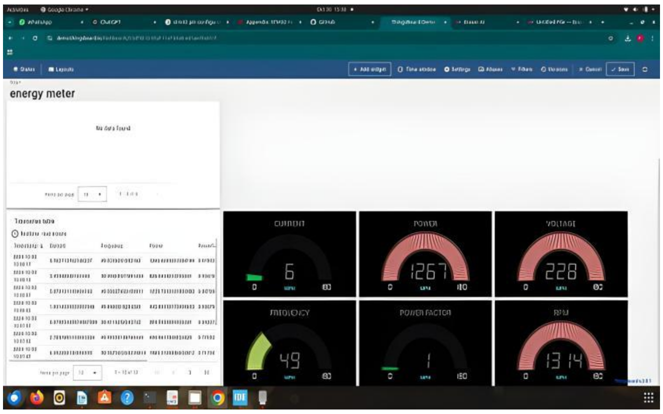

Fig.5 – Real-Time Energy Monitoring Dashboard in ThingsBoard

B. Actual vs Predicted Anomaly Comparison

The identification of anomaly electrical energy consumption directs a pivotal strategy for targeting extensive energy efficiency, offering multifarious benefits that goes beyond mere energy savings. The Fig. 6.1 and 6.2 has the actual vs predicted anomalies compares actual and predicted anomalies to assess our model's accuracy in detecting energy consumption irregularities for frequency, RMP, energy vs time and current, power, voltage vs time with anomaly detection respectively.

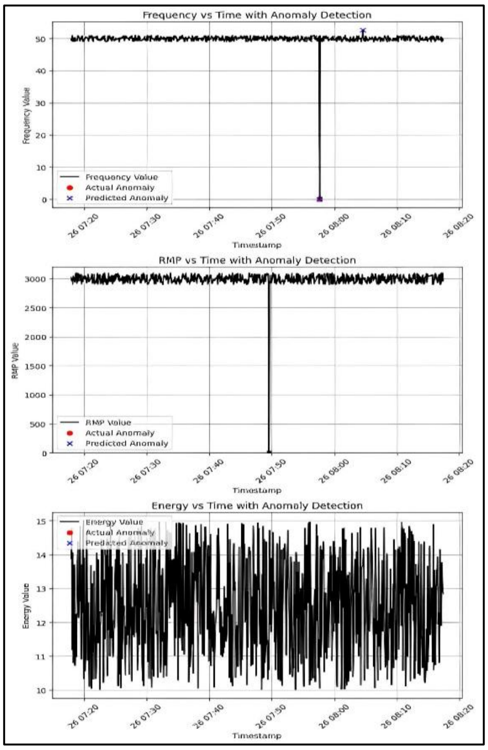

Fig.6.1–Comparison of Actual and Predicted Anomalies

Using predefined thresholds, actual anomalies were identified, while the TensorFlow model predicted deviations based on learned patterns. The model effectively detects major fluctuations in energy, current, and power, though minor discrepancies highlight the need for threshold optimization and better feature extraction.

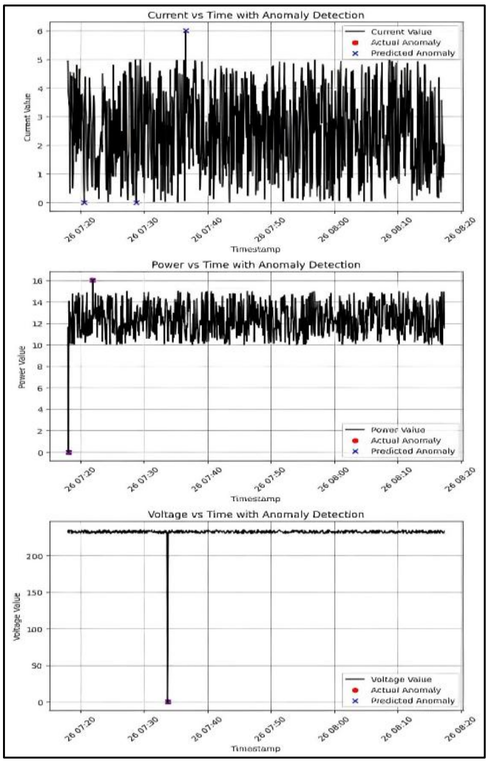

Fig.6.2–Comparison of Actual and Predicted Anomalies

C. Statistical Analysis of Anomaly Detection

The anomaly detection performance across six key industrial parameters Frequency, Current, RMP, Power, Energy, and Voltage is summarized in Table 1.

Table 1: Anomaly Detection Summary

Key	**Total Points**	**Actual Anomalies (%)**	**Predicted Anomalies (%)**
Frequency	714	0.140056	0.280112
Current	714	0.420168	0.380224
RMP	714	0.140056	0.180112
Power	714	0.280112	0.340168
Energy	714	0.000000	0.000000
Voltage	714	0.140056	0.200168
Overall	**4999**	**47.06**	**50.94**

The model effectively detects anomalies, with predicted values closely aligning with actual ones across multiple parameters. Frequency shows a slight overestimation (0.28% vs. 0.14%), ensuring a conservative approach. Current anomalies are slightly under-predicted (0.38% vs. 0.42%), while RPM and Power exhibit small deviations between actual and predicted values (0.14% vs. 0.18% for RPM and 0.28% vs. 0.34% for Power). Voltage also shows a minor difference (0.14% vs. 0.20%), indicating a slight over-detection. Notably, Energy has no anomalies, confirming stability in that aspect. The overall predicted anomaly rate (50.94%) slightly exceeds the actual anomaly rate (47.06%), ensuring a robust detection system that minimizes false negatives. Fig. 7 provides a visual representation of this comparison.

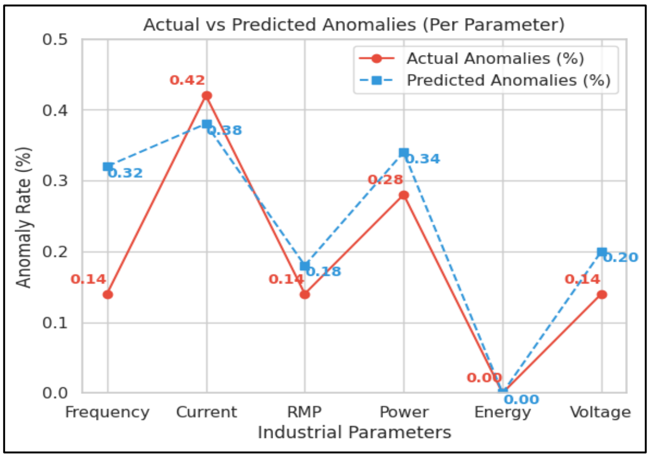

Fig.7: Statistical Comparison of Actual vs. Predicted Anomalies

D. Predictive Bill Estimation

Our system analyzes electricity costs over a 59.42-minute interval, considering a unit consumption of 3.27 kWh as shown in Table 2. Using real-time monitoring and automated alerts via ThingsBoard, users are notified of cost variations, enabling proactive energy management.

The tariff rates used in this analysis are derived from established references, including Rai et al. (2013) [16], Gavit et al. (2022) [17], PHD Research Bureau (2011) [18], and NITI Aayog (2017) [19], which provide a comprehensive overview of industrial electricity pricing structures in India.

Table 2: Cost Estimation for Varying Tariffs

Tariff (₹/kWh)	Total Cost (₹)	Time Interval (minutes)	Unit Consumption (kWh)	Type of Rate
6.9	22.59	59.42	3.27	Base Rate
6.72	22.0	59.42	3.27	Optimized Rate
7.39	24.19	59.42	3.27	Peak-hour Rate
8.1	26.52	59.42	3.27	High-Demand Rate
9.56	31.3	59.42	3.27	Premium Rate
7.85	25.7	59.42	3.27	Intermediate Rate

In Fig. 8, the comparison of electricity costs under different tariff rates for a 59.42-minute operation (3.27 kWh) is depicted. The Optimized Rate (₹6.72/kWh) minimizes costs (₹22.00), while the Premium Rate (₹9.56/kWh) peaks at ₹31.30, triggering an alert for high cost. Similarly, the High-Demand Rate (₹8.10/kWh, ₹26.52) will also generate an alert, indicating a significant cost increase. The inference from the Fig.8 clearly depicts that, when tariffs rates increase at specific intervals for premium or high demand rate, end users will be alerted about rise in the elevated costs through system-level alerts and ThingsBoard user interfaces.

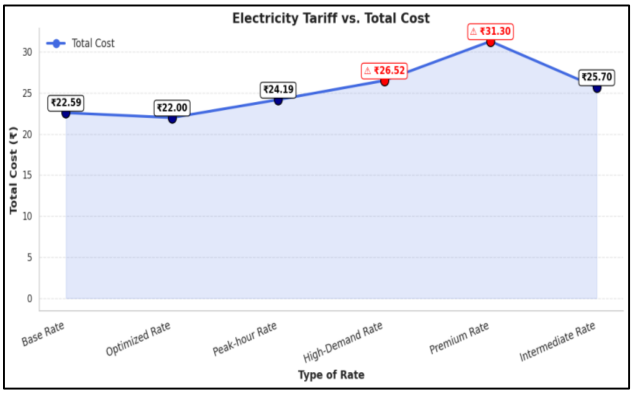

Fig 8 - Predictive Bill Estimation Based on Varying Tariffs

IV. Conclusions

This research work implements an Advanced Industrial Energy Monitoring System that integrates IoT and embedded systems to enable real-time energy monitoring, anomaly detection, and predictive analysis. By leveraging an STM32F446RE microcontroller, Modbus RTU communication, and Bluetooth connectivity to a rugged board, the system efficiently collects and transmits telemetry data to ThingsBoard for visualization and analysis. The implementation of anomaly detection using TensorFlow provides early indications of irregular energy consumption patterns, facilitating proactive maintenance and energy optimization. Additionally, the predictive bill analysis model offers insights into future energy costs, assisting industries in financial planning. The system's modular design ensures adaptability for various industrial environments, making it a scalable and reliable solution for energy management. This framework can integrate real-time data from the electricity service provider API for dynamic pricing, enhancing the predictive accuracy of energy cost estimations. This would allow the system to adjust predictions based on actual utility data, improving the system's responsiveness to real-world changes in tariff rates. Additionally, if the tariff increases during certain intervals, both system-level alerts and ThingsBoard notifications will be triggered to inform users of the high costs, providing an opportunity for timely action.

V. Acknowledgement

The authors gratefully acknowledge the support from Dayananda Sagar University, Karnataka, and PHYTEC Embedded Pvt. Ltd. for providing the necessary equipment, resources and insights for this research.

VI. References

[1] O'Driscoll, E., & O'Donnell, G. E. (2012). Industrial power and energy metering – a state-of-the-art review. Journal of Cleaner Production, 41, 53–64. https://doi.org/10.1016/j.jclepro.2012.09.046

[2] Salvadori, F., De Campos, M., Sausen, P., De Camargo, R., Gehrke, C., Rech, C., Spohn, M., & Oliveira, A. (2009). Monitoring in industrial systems using wireless sensor network with dynamic power management. IEEE Transactions on Instrumentation and Measurement, 58(9), 3104–3111. https://doi.org/10.1109/tim.2009.2016882

[3] Design of an industrial IoT-Based monitoring system for power substations. (2019, December 1). IEEE Journals &Magazine IEEEXplore. https://ieeexplore.ieee.org/abstract/document/8828071

[4] Sung, W., & Hsu, Y. (2010). Designing an industrial real-time measurement and monitoring system based on embedded system and ZigBee. Expert Systems with Applications, 38(4), 4522–4529. https://doi.org/10.1016/j.eswa.2010.09.126

[5] Mudaliar, M. D., & Sivakumar, N. (2020). IoT based real time energy monitoring system using Raspberry Pi. Internet of Things, 12, 100292. https://doi.org/10.1016/j.iot.2020.100292

[6] Herath, H., Ariyathunge, S., & Priyankara, H. (2020). Development of a data acquisition and monitoring system based on MODBUS RTU communication Protocol. International Journal of Innovative Science and Research Technology (IJISRT), 5(6), 433–440. https://doi.org/10.38124/ijisrt20jun479

[7] Design of home energy saving monitoring system based on STM32. (2024, June 14). IEEE Conference Publication | IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/10674241

[8] Su, Y. (2024). An intelligent heating system based on the Internet of Things and STM32 microcontroller. Energy Informatics, 7(1). https://doi.org/10.1186/s42162-024-00326-2

[9] Salunkhe, A. S., Kanse, Y. K., & Patil, S. S. (2022). Internet of Things based Smart Energy Meter with ESP 32 Real Time Data Monitoring. 2022 International Conference on Electronics and Renewable Systems (ICEARS),446–451. https://doi.org/10.1109/icears53579.2022.9752144

[10] Chen, R., Zhang, Y., & Liu, J. (2016). Design of remote industrial control system based on STM32. In Springer eBooks (pp. 257–267). https://doi.org/10.1007/978-3-319-44350-8_26

[11] Thakur, S. (2023). IoT Based on Industry Power Status Monitoring and Alert Systems using RaspberryPI and Thingsboard. International Journal for Multidisciplinary Research, 5(6). https://doi.org/10.36948/ijfmr.2023.v05i06.8422

[12] Rajput, S., Widmayer, T., Shang, Z., Kechagia, M., Sarro, F., & Sharma, T. (2024). Enhancing Energy-Awareness in Deep Learning through Fine-Grained Energy Measurement. ACM Transactions on Software Engineering and Methodology. https://doi.org/10.1145/3680470

[13] Liu, Y., Garg, S., Nie, J., Zhang, Y., Xiong, Z., Kang, J., & Hossain, M. S. (2020). Deep anomaly Detection for Time-Series Data in Industrial IoT: A Communication-Efficient On-Device federated Learning Approach. IEEE Internet of ThingsJournal,8(8),6348–6358. https://doi.org/10.1109/jiot.2020.3011726

[14] Henschke, M., Wei, X., & Zhang, X. (2020). Data Visualization for Wireless Sensor Networks Using ThingsBoard. 2020 29th Wireless and Optical Communications Conference (WOCC). https://doi.org/10.1109/wocc48579.2020.911492

[15] Robles-Durazno, A., Moradpoor, N., McWhinnie, J., & Russell, G. (2018). A supervised energy monitoring-based machine learning approach for anomaly detection in a clean water supply system. 2018 International Conference on Cyber Security and Protection of Digital Services. https://doi.org/10.1109/cybersecpods.2018.856

[16] J. N. Rai, R. K. Gupta, R. Kapoor, and R. Garai, "Tariff Setting in the Indian Power Sector— An Overview," IOSR Journal Of Electrical and Electronics Engineering, vol. 6, no. 1, pp. 97–108, 2013.

[17] K. S. Gavit, K. G. Dhomse, A. Mishra, and P. C. Tapre, "Smart Tariff Controller Based Energy Bill Optimization for Industrial Applications," JETIR, vol. 9, no. 4, pp. 347–352, 2022.

[18] PHD Research Bureau, "An Analysis of Power Tariffs Across India," PHD Chamber of Commerce and Industry, 2011. https://www.phdcci.in/wp-content/uploads/2018/11/An-Analysis-of-Power-Tariffs-Across-India.pdf

[19] NITI Aayog, "Electricity Tariff Trends in India," NITI Aayog, 2017. https://library.niti.gov.in/electricity-tariff-trends-india