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EV Monitoring and Optimizing Platform

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Abstract: *The rise of the use of Electric Vehicles (EVs) has been a scalding question in terms of its failure, energy inefficiency, and improper planning of its locations. The issues result in efficiency and user experience issues. The current paper proposes an EV Monitoring and Optimizing Platform, the cloud-based service that is the integration of artificial intelligence (AI), Internet of Things (IoT), and big data technologies. The platform is implemented with the use of IoT sensors to monitor the performance of the charging stations in real-time to conduct fault-proactive and predictive maintenance. Even the active and effective charging management is informed by the analysis on the basis of this data and the further expansion of infrastructure is informed by it. Consequently, the offered system will make EV charging networks more efficient and reliable, and will simplify the decision-making of city authorities and operators of services and will allow offering a better overall charging experience to the users*

Keywords: Smart EV Charging, Edge Computing (Sensors), Big Data Analytics (Traffic & Usage Data), Cloud Computing (IoT & AI Services), Predictive Maintenance, Fault Detection, Infrastructure Optimization

I. INTRODUCTION

With the explosive increase in electric vehicles (EVs), the need to have efficient and reliable electric charging infrastructure has increased. Nevertheless, existing EV charge systems are associated with problems like unpredictable system malfunctions, energy waste, ineffective use of stations, and ineffective planning of infrastructure. These problems deteriorate the experience of users as well as make the work of service providers more expensive.

The current system of charging management embraces a reactive monitoring approach, such that faults are only fixed after they have taken place. These systems tend to be based on remote data sources and central processing, which leads to slow response time and a lack of scalability. The latest developments in IoT, cloud computing, and big data analytics provide an opportunity to gather data in real-time and analyze it on a large scale; however, solutions based only on cloud computing are characterized by latency in time-sensitive failure cases.

To resolve these deficiencies, the present paper proposes an EV Monitoring and Optimizing Platform, which is an IoT sensor-based platform that uses edge computing technology, cloud computing, big data analytics, and Agentic AI. The system enables real time visibility, predictive fault detection, automated response to charging anomalies and planning in the industry. The system will enhance the reliability, reduce the response time, and enhance energy efficiency in EV charging networks through the combination of edge-level intelligence and cloud-based intelligence .

1. Contribution of This Paper:

This paper will make following contributions:

a. Proposes an IoT-based, Big Data, and Agentic AI autonomous fault response cloud-edge EV charging monitor architecture..

b. Trains an A.I. predictive fault detection pipeline using real-time sensor information of charging stations.

c. Uses edge-based anomaly detection to reduce the response time in case of charging failure..

d. Evaluates the system when used in the simulation of cases of EV charging and compares the system to the traditional systems in reactive monitoring.

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II. PROPOSED SYSTEM

The proposed EV Monitoring and Optimizing Platform aims to support real-time monitoring, predictive fault detection as well as autonomous response to EV charging infrastructure. The system incorporates IoT sensing, edge computing, cloud-based analytics, big data processing, and Agentic AI in a single architecture to eliminate the constraints of reactive and cloud-only charging management systems.

1. System Architecture Design

The platform conforms to layered cloud-edge architecture, which has four primary functional layers.

1.1 IoT Sensing Layer:

EV charging stations are equipped with sensors and the continuity of the sensor is such that it captures the operational parameters such as voltage, current, temperature and time required to charge. They are stream sensor and foundation of the intelligence of the system and enable trace finely of the health and usage behavior of the stations

1.2 Edge Computing Layer:

The preprocessing of real-time date and anomaly detection on the local edge nodes are conducted with Raspberry PI 4 and other sensors that are also installed on the AWS IoT Greengrass. On-device inference is possible to monitor abnormal conditions (e.g. voltage spikes or overheating) as soon as they occur. In emergency cases, the edge node activates safety protocols like shutting down chargers, and sending an alert to the cloud, even with the limited network connectivity.

1.3 Cloud and Big Data Analytics Layer:

The data of several charging stations are aggregated and sent to the cloud to perform the processing of large volumes and long-term analytics. Apache Spark Apache Spark is scalable and may be used to analyze both real-time and batch analytics on heterogeneous data (applicable to sensor readings, traffic flow, and environmental data). InfluxDB is used to store time-series charging logs whereas structured metadata is saved in AWS RDS (PostgreSQL). The layer is useful in predictive maintenance modeling, usage trend analysis, and optimization of infrastructure.

1.4 Agentic AI Layer:

The Agentic AI element is capable of working on processed information and faults identified to generate autonomously corrective recommendations, maintenance schedules, and intelligence on infrastructure expansion. This layer allows dynamic and smart decision-making in the charging network by decreasing the use of manual intervention.

This multi-layered design introduces scalability, modularity and low response latency to faults and is ideal in massive and geographically distributed EV charging networks.

2. Edge computing Latency Model and Advantage:

To investigate system responsiveness, the total response latency L is a follows:

$L = L_{edge} + L_{network} + L_{cloud}$

where, L_{edge} represents processing time at edge,

$L_{network}$ represents delay of communication, and

L_{cloud} makes use of cloud processing time.

The two have been reduced to a minimum by the proposed system which does an anomaly detection and preliminary fault response at the edge. In fault situations, $L_{network}$ and L_{cloud}, it enables faster response as compared to traditional cloud-only approaches to monitoring.

3. Evaluation Strategy

The system is checked regarding the simulated multi-station EV charging conditions under various conditions of traffic load and environmental conditions. The performance metrics include the fault detection rate, response time, energy usage and scalability. The effectiveness of the proposed cloud-edge design is determined by comparing the outcomes with the conventional reactive monitoring designs.

4. Algorithm

Fault Detection and response Edge-Based.

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Input:
Sensor data stream SSS (voltage, current, temperature)
Output:
Status of fault and action of response.
Pseudocode:

```
For each incoming sensor data packet in S do:
    Acquire  voltage, current, and temperature
    Compute edge-based model of anomaly score.
    If anomaly score > predefined threshold then:
        Close the charging station in question.
        Send fault alarm to cloud server
        Corrective Trigger Agentic AI.
         Recommendation
    Else:
         Keep on with charging as usual.
End For
```

III. RESULTS

1. Dataset Description and Experimental Setup

To evaluate the efficiency of the proposed EV Monitoring and Optimization Platform, simulated multi-station charging data was generated. The simulation represented five electric vehicle charging stations operating continuously over a period of 30 days. Time-series data for key operational parameters-voltage, current, temperature, charging duration, and total energy consumption- was collected to closely reflect real-world conditions. The dataset included both normal charging behavior and intentionally introduced fault scenarios, such as voltage instability, abnormal current patterns, and thermal irregularities.

These fault situations were designed based on failure modes commonly observed in EV charging infrastructure. For model development and validation, the dataset was divided using a 70:30 training-to-testing ratio. In addition, edge-level inference was simulated to replicate deployment in real environments using resource-constrained hardware platforms, such as edge devices built on the Raspberry Pi.

2. Performance Metrics

Here are the points to measure KPIs :

Response Latency: Measures the duration of time that elapses between the occurrence of fault and the response of the system

Fault Detection Precision: Fraction of detected fault events.

Energy Efficiency Improvement: Percentage decrease on energy wastage.

Scalability: Stability of the system with the added charging load.

3. Response Latency Analysis

Experimental analysis showed that the proposed platform achieved an average end-to-end response latency of approximately 1.2 seconds, even under heavy charging load conditions. For comparison, a cloud-only monitoring system was also evaluated and demonstrated a higher average response time of 1.9 seconds, mainly due to communication overhead and delays caused by centralized computation. Similarly, a traditional threshold-based monitoring approach exhibited even greater latency, reaching about 2.8 seconds, as a result of periodic polling and manual alert procedures. These results provide evidence that edge-assisted intelligence is an important factor in reducing the delays of responses, which leads to quick fault management in time-sensitive EV charging systems.

4. Fault Detection Accuracy

The preciseness of the AI-based fault-detecting aspect in the proposed platform was about 87 percent, which means that the system is reliable to identify the abnormal charging patterns which could be a voltage or overheating incident and abnormal current distribution. Comparatively, the threshold-based approach of monitoring achieved lower precision of 71 percent indicating their inability to accommodate the different operating conditions. The precision of the cloud-only AI-based system was 82% other than being less successful in times of high system load because of response delays. Automatic response was made possible by recognition of the faults in time, which led to the shutdown of the chargers and the generation of real-time alerts.

5. Energy Optimization Evaluation

The EV monitoring platform proposed reached an approximate 14% decrease in energy waste due to the intelligent management of the charging process and the active prevention of faults. The savings of energy were achieved through the detection of inefficient charging sessions, prevention of long-term working in unhealthy conditions, and optimization of the length of the charging process based on real-time analytics. Baseline monitoring systems on the other hand were mainly based on reactive responses and could not anticipate fault events, and therefore the system incurs more losses in the event of fault.

6. Comparative Performance Summary

A comparative evaluation of the proposed platform against baseline approaches is summarized in Table 4.6.1.

Method	Fault Detection Precision	Avg. Response Latency
Threshold-based Monitoring	71%	2.8 s
Cloud-only AI Monitoring	82%	1.9 s
Proposed Edge + AI Pl	87%	1.2 s

Table 4.6.1 : Performance Comparison of Monitoring

The results indicate that the proposed platform consistently outperforms baseline systems in both accuracy and responsiveness.

7. Visualization and Monitoring Interface

The system also provided operator oriented monitoring interface that enabled visualization of real-time charging station status, charging process, energy consumption trend together with fault alert. These graphic enlightenments enhanced situational awareness and assisted faster and more correctly informed operational choice of system administrators and service providers.

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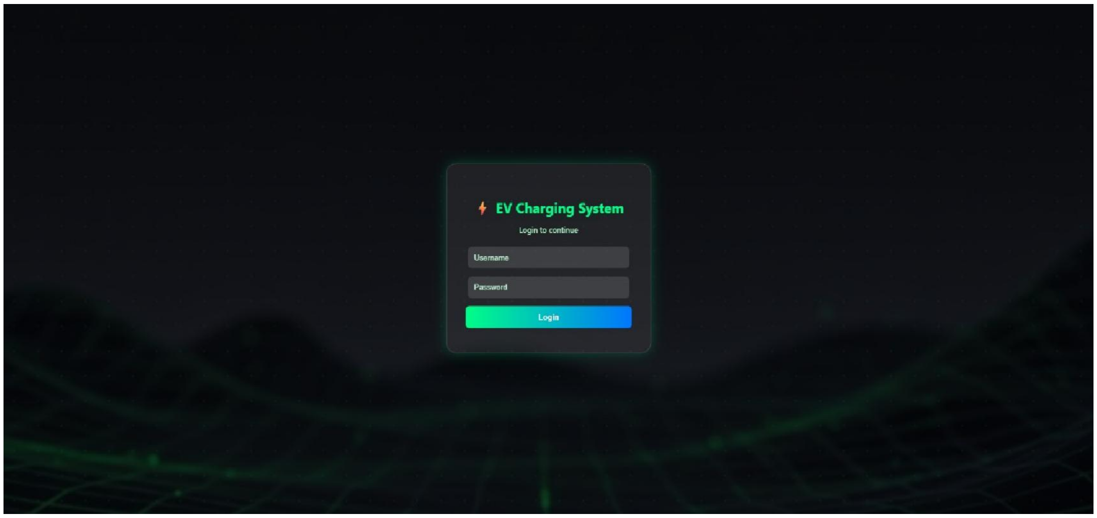

Figure 2: Login Page

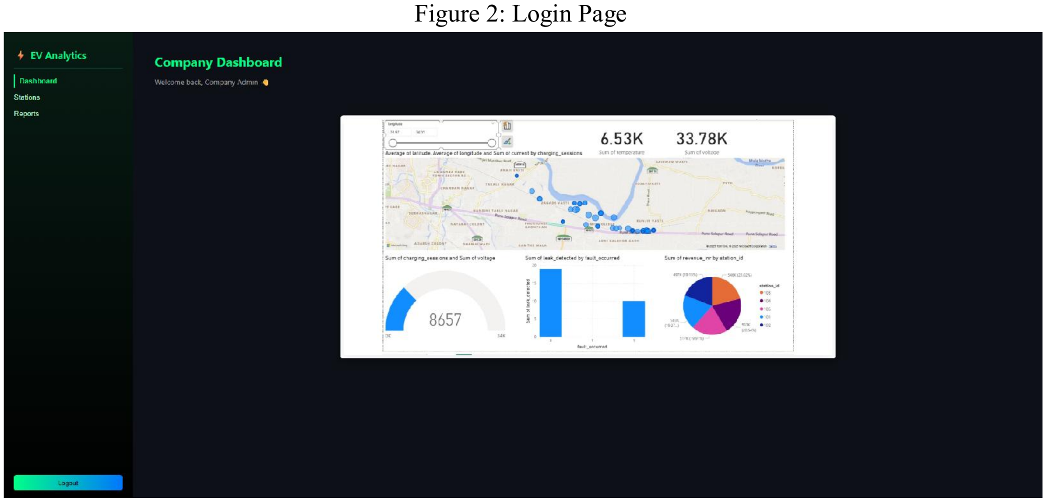

Figure 3: Company Admin Dashboard

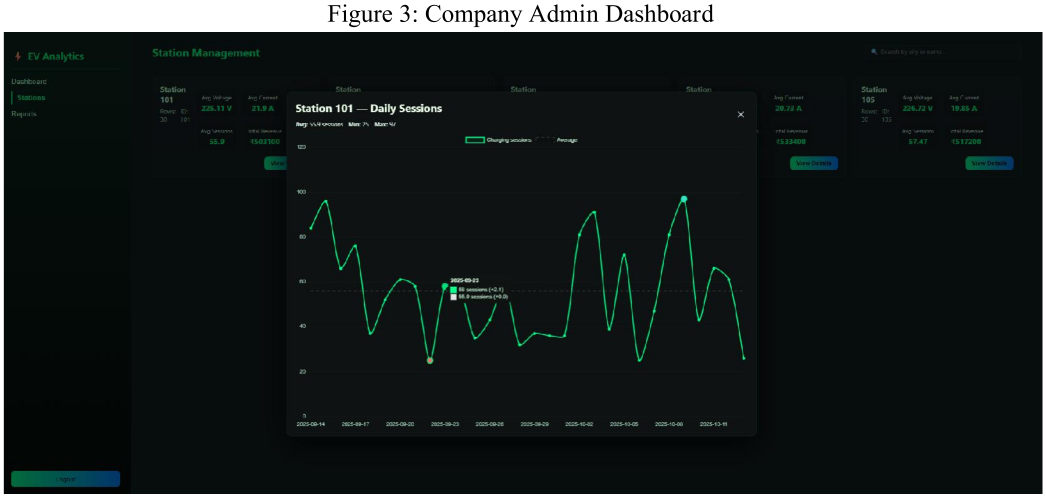

Figure 4: All Station Reports

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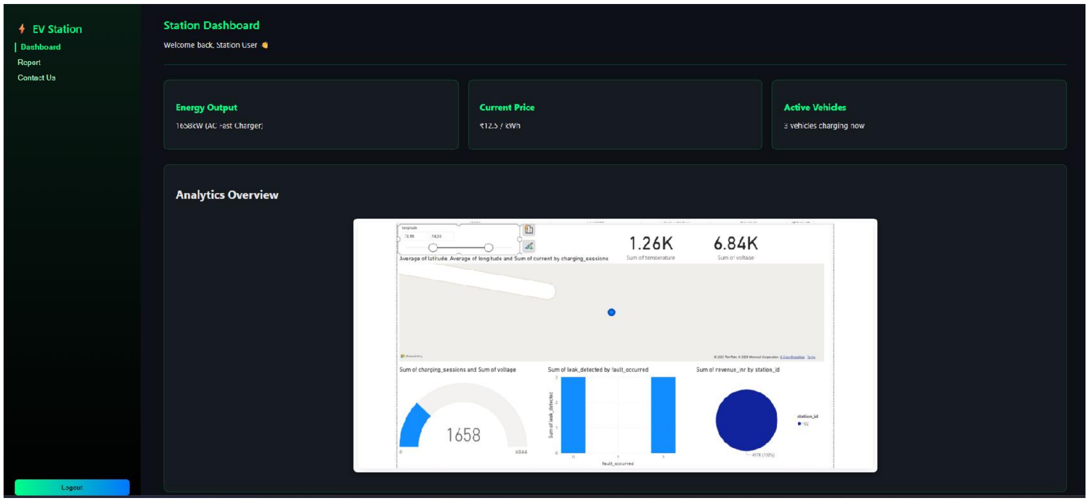

Figure 5: Station User Dashboard

IV. CONCLUSION

The paper introduces the design and development of a smart EV Monitoring and Optimization Platform aimed at addressing major flaws in the current electric vehicle charging system. The proposed system integrates real time thought Iot, cloud based data management, big data analytics and AI driven intelligence to transform conventional charging networks into predictive and adaptive system. By continuously monitoring charging stations and analyzing information intelligently, the platform enhances system visibility, support informed decision making and strengthens the foundation of reliable and trustworthy EV charging infrastructure.

Experimental evaluation in a simulated scenario demonstrates that the platform improves system performance in terms of response time, fault detection accuracy and overall efficiency. The system enable early identification of abnormalities and optimizes charging operation using data driven insight, helping to reduce unplanned downtime and energy loss. These capabilities support service providers and city planners in improving infrastructure reliability, optimizing resource utilization and making better decisions regarding future network expansion.

Beyond operational advantages, this work emphasizes the importance of scalable cloud and edge computing architecture for handling the rapidly increasing volume of EV-related data. The platform’s modular design makes it possible to extend to large deployments with minimal modification. However , the current implementation has primarily been validated in simulated environments. Future work will therefore concentrate on real-world deployment, deeper integration with smart grid systems, and the incorporation of renewable energy sources to further enhance the system’s practicality and impact.

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We would like to show appreciation to everyone that was part of the development process of the EV Monitoring and Optimizing Platform. We would specifically like to thank the students and teachers who were kind enough to participate and gave us feedback that allowed us to orient the platform toward community's needs. We are also very grateful for the interaction we had with EV station operators, handlers, and customers during our field research-the input, practical feedback and suggestions from their real world experience was key to determine the best features and design for our system.

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