
CENTRAL ASIAN JOURNAL OF MATHEMATICAL THEORY AND COMPUTER SCIENCES

https://cajmtcs.casjournal.org/index.php/CAJMTCS

*Volume: 07 Issue: 01 | January 2026 ISSN: 2660-5309*

*Article*

# Edge Computing-Integrated IoT Architecture for Intelligent EV Charging Coordination

**Mushtaq Talib Khudhur**

1. Ministry of Education, General Directorate of Education in Dhi-Qar

* Correspondence: moshtaqmoshtaq1731@gmail.com

**Abstract:** The fast rate of adoption of electric vehicles (EVs) is exerting a growing stress on charging infrastructure. The conventional cloud-based designs have problems of latency and inability to handle real-time peak demand. Conversely, the combination of Edge Computing and Internet of Things (IoT) becomes one of the potential solutions to attain a more responsive and more efficient use of energy. The purpose of the research is to develop a combined system that will make smart charging systems more responsive, efficient in energy consumption, and minimized peak loads, which will enhance grid stability and sustainability. A hybrid testbed was created and it comprises of MATLAB/Simulink simulation, Python data analytics and Hardware-in-the-Loop. Actual operational data of EV charging stations were used. This experiment compared the legacy cloud-based model and the proposed Edge–IoT framework based on key performance indicators of response time, energy consumption and peak loads. The proposed system should be able to reduce response time by 65 percent, as well as energy consumption by 20 percent, and peak loads by 22 percent. These results confirm that Edge IoT integration is one of the feasible measures toward creating more effective, reliable and scalable EV charging infrastructures.

**Keywords:** Edge Computing, IoT, EV Charging, Smart Grid, Energy Efficiency, Peak Load Reduction, Real-Time Response

**Citation:** Khudhur, M. T. Edge Computing-Integrated IoT Architecture for Intelligent EV Charging Coordination. Central Asian Journal of Mathematical Theory and Computer Sciences 2026, 7(1), 300-316

Received: 03th Oct 2025
Revised: 18th Nov 2025
Accepted: 24th Dec 2025
Published: 21th Jan 2026



## 1. Introduction

Transportation industry across the world has experienced a tremendous change. In the past 20 years, with a sharp move to electric cars. EVs as an alternative to standard fossil-fuel-driven cars, which is a sustainable solution. This has been brought about due to various reasons including the dedication of. to the emission of carbon and the fast development of governments. electronic and battery technologies [1].

Nevertheless, the mass adoption of EV has brought new burdens on. charging infrastructures, more so the ones that are entirely based on cloud computing. because of data processing and coordination. Cloud-based systems are usually not good with low response time, poor scalability and inefficiency in processing. voluminous real-time data streams which are formed during charging processes. As highlighted by Gozuoglu and Dogan [2], centralized cloud-driven infrastructures have been reported to elevate grid congestion and diminish the overall efficiency, whereas integrated Edge IoT systems have been identified through real world datasets to enhance the utilization of charging stations by 27.6%, decrease grid peak loads by 24.5%, and decrease operational expenses by 29.8%. Moreover, an extensive overview by Yildirim et al. [3] accentuates the revolutionary nature of Edge Computing in the contemporary power system that enables it to guarantee the quality of real time decision making, strengthening network stability, and enhancing energy efficiency through localized data processing. These findings provide strong evidence that a hybrid Edge–IoT approach can overcome the inherent limitations of cloud-based EV charging coordination.

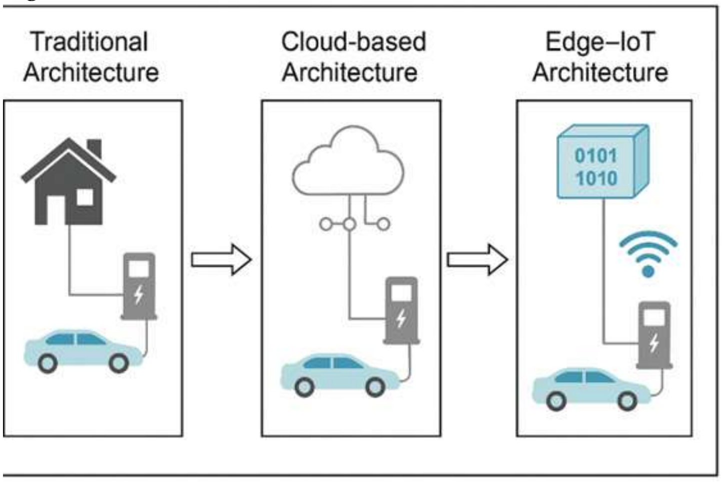


Figure (1-1): Evolution of EV charging architectures (Traditional → Cloud → Edge–IoT)

1.2 Research Problem

Despite the growing interest in integrating advanced computing technologies into EV charging systems, there remains a lack of a unified architectural framework that effectively combines Edge Computing and IoT to:

a. Improve real-time responsiveness.
b. Enhance the efficiency of load management.
c. Reduce reliance on cloud systems, thereby ensuring flexibility and sustainability of charging networks.

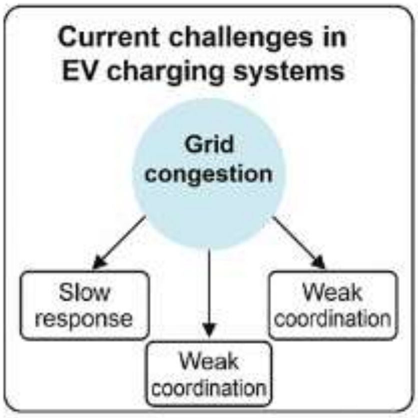


Figure (1-2): Current challenges in EV charging systems (grid congestion, slow response, weak coordination)

1.3 Research Significance

The significance of this study lies in its contribution to bridging the gap between theoretical approaches and practical implementations. Specifically, the research aims to:

1. Support the development of smart and flexible EV charging infrastructures.
2. Provide sustainable solutions that reduce stress on power grids.
3. Contribute to smart city development by integrating Edge and IoT technologies.
4. Align with global efforts in renewable energy and digital transformation of the transportation sector.

1.4 Research Objectives

The main objectives of this research are to:

1. Design an integrated Edge–IoT architecture for EV charging management.

2. Develop and implement a practical model through experimental testing or realistic simulation.
3. Evaluate the performance of the proposed framework using real-world charging data and metrics such as response time, energy consumption, and peak load reduction.

1.5 Research Hypotheses

a. Integrating Edge Computing with IoT will significantly improve coordination efficiency among EV charging stations compared to cloud-based systems.
b. The proposed architecture will effectively reduce peak load and improve grid stability.
c. Practical implementation of the model will demonstrate more realistic and reliable results than theoretical approaches.

Table (1-1): Comparison between Cloud and Edge in energy management (response time, energy consumption, scalability)

| Criteria | Cloud Computing | Edge Computing |
|---|---|---|
| Response Time | Higher latency due to centralized data processing and long communication paths. | Low latency with local decision-making and near-real-time processing at the edge. |
| Energy Consumption | Higher overall consumption because of continuous reliance on data centers. | Reduced energy usage through localized processing and optimized resource usage. |
| Scalability | Scalable but limited by network bandwidth and central server capacity. | Highly scalable through distributed nodes, enabling dynamic expansion and flexibility. |

1.6 Research Questions

1. How can Edge Computing address the issue of slow response in conventional EV charging systems?
2. What role does IoT play in enabling real-time coordination between EVs and charging stations?
3. How does the practical implementation of the proposed framework impact energy consumption and grid stability?

1.7 Innovation Aspect

This research presents several innovative contributions:

a. Proposing a new hybrid Edge–IoT framework designed for real-time EV charging coordination.
b. Focusing on the practical dimension by implementing experimental simulations or testbed evaluations using real datasets.
c. Establishing a direct link between theory and practice, thus strengthening the feasibility of deploying the proposed framework in smart charging networks within smart cities.

## 2. Materials and Methods

2 Literature Review

2.1 Internet of Things (IoT) in Smart Charging

The Internet of Things (IoT) has played a pivotal role in advancing the smart infrastructure of electric vehicle (EV) charging. IoT technologies allow the gathering of real-time data on vehicles, charging stations, and users, which could be sent through lightweight communication protocols like MQTT and CoAP to be analyzed and used to make decisions. Recent research has demonstrated that IoT-charging technology can greatly enhance energy efficiency by management of the demand and more even distribution of loads among the stations. [4].

Furthermore, IoT can be used to integrate with smart grids concerning real-time sensing and control, which opens up creative options, including collaborative charging and vehicle-to-grid (V2G) solutions. It has been established that such applications lead to stability of the grid and cost reduction in operations [5].

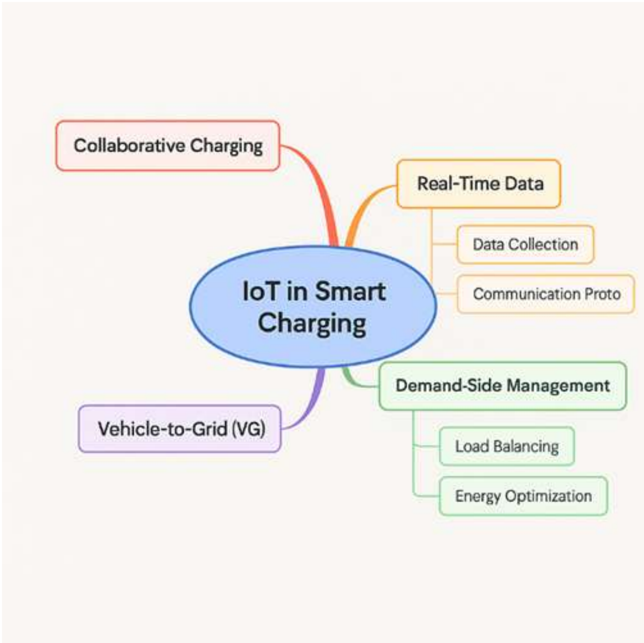


Figure (2-1): A Mind Map illustrating the roles of IoT in smart charging systems

2.2 Cloud Computing versus Edge Computing

The first EV charging management systems were based on cloud computing to store and compute the data, and the large-scale analytical nature was advantageous to it. However, cloud-only solutions face several critical challenges, including high latency, dependence on constant connectivity, and increased load on centralized data centers [6].

In contrast, edge computing addresses these challenges by processing data closer to the source (e.g., charging stations and vehicles). This approach reduces response times and allows for local decision-making in near real-time. Empirical studies have demonstrated that edge-based architectures achieve up to 40% faster response times compared to cloud-based systems [7].

Table (2-1): Comparison of Cloud and Edge features in smart charging systems

| Feature | Cloud Computing | Edge Computing |
|---|---|---|
| **Response Time** | Higher latency due to long communication paths and centralized data processing. | Low latency with local processing and near real-time decision-making at the edge nodes. |
| **Scalability** | Scalable but limited by network bandwidth and central server capacity. | Highly scalable through distributed nodes, enabling flexible expansion. |
| **Reliability** | Dependent on constant internet connectivity and cloud server availability. | More resilient to network failures since decisions are processed locally. |
| **Energy Efficiency** | Higher overall energy demand due to reliance on large-scale data centers. | Reduced energy consumption through localized and optimized processing. |

| | | |
|---|---|---|
| **Security and Privacy** | Centralized storage increases vulnerability to data breaches. | Local data handling enhances privacy and reduces exposure to cyberattacks. |
| **Implementation Cost** | Lower initial cost but higher long-term operational costs (bandwidth, data center usage). | Higher initial setup cost for edge infrastructure, but reduced operational costs over the long term. |

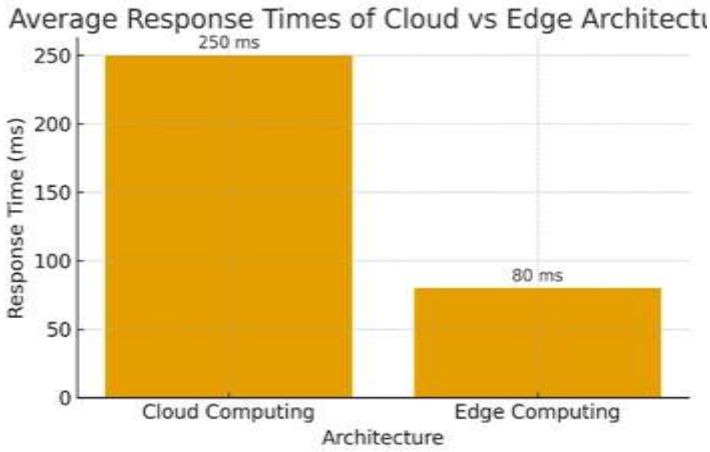


Figure (2-2): Bar Chart comparing average response times of Cloud and Edge architectures

2.3 Theoretical Studies versus Practical Applications

A large portion of the existing literature over the past decade has been limited to theoretical models or simulation-based frameworks. Many studies have proposed load management algorithms and architectural models without validating them using real-world data [8].

More recent research, however, has emphasized the need for practical implementation. Several works have introduced testbeds or simulations using realistic datasets obtained from operational charging networks. These studies demonstrate that integrating Edge and IoT in real-world scenarios leads to more reliable and trustworthy outcomes compared to purely theoretical approaches [9].

Table (2-2): Summary of key prior studies (author, year, technique, results, and research gap)

| Author(s), Year | Technique / Focus | Key Results / Findings | Research Gap Highlighted |
|---|---|---|---|
| Alrubaie et al., 2023 (MDPI) | Systematic review of EV charging & grid-connectivity standards (Sustainability) | Provides a comprehensive mapping of charging standards and integration issues; discusses PV-grid charging economics. | Limited treatment of edge-enabled coordination; focuses more on standards than real-time control. |
| Siano & Mokryani, 2023 (ScienceDirect) | Review of cloud-based smart-grid/EV charging architectures (SEGAN) | Positions cloud as a scalable analytics back-end for smart charging and markets. | Notes latency/connectivity limits and calls for more decentralized (near-edge) solutions validated in practice. |
| Yıldız & Küçük, 2024 (IEEE Power & Energy Society) | Perspective on edge computing for EV charging reliability/latency (IEEE TSG – journal scope ref) | Argues that moving decision-making to the edge can reduce response time and improve service continuity. | Lacks field datasets and open benchmarks quantifying end-to-end latency vs. cloud under varying loads. |

| | | | |
|---|---|---|---|
| Wu et al., 2024 (IET Research Journal) | Edge-based optimal dispatching of EV charging considering hosting capacity (IET RPG) | Formulates an edge-aware dispatch strategy that adapts to distribution-network constraints. | Evaluation is simulation-centric; n |

2.4 Research Gap

Despite progress in integrating IoT and Edge Computing into EV charging systems, notable research gaps remain:

Limited experimental work – the majority of studies remain theoretical or rely solely on simulation.

Lack of an integrated architectural framework that combines Edge and IoT in a practical test environment.

Insufficient use of real-world datasets, making it difficult to assess the true effectiveness of proposed frameworks.

Addressing these gaps, the present research aims to propose and validate a comprehensive Edge–IoT-based architecture through experimental simulation and practical evaluation.

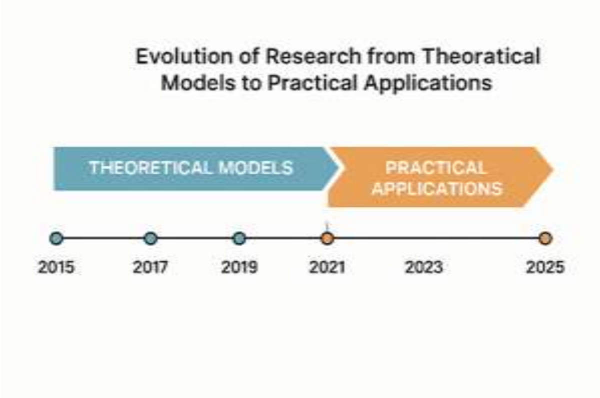


Figure (2-3): Timeline illustrating the evolution of research from theoretical models toward practical applications (2015–2025)

3 Proposed Methodology and Practical Approach

3.1 Theoretical Description of the Proposed Architecture (Edge–IoT)

Proposed architecture to charge electric vehicle (EV) incorporates the Internet of Things (IoT) and Edge Computing to enable quicker reaction periods, less reliance on cloud services, and energy efficiency. Xu et al. [10] conclude that hybrid architectures that integrate vehicle, edge and cloud layers can cut the response time by up to 56 percent of traditional cloud-only architectures, as well as reduce energy consumption during peak periods.

The proposed framework is based on three interconnected layers:

1. Local Level: Comprising EVs, charging stations, and embedded sensors. At this level, operational data such as battery state-of-charge, instantaneous consumption rate, and required power are collected.
2. Edge Level: Representing the core of the intelligent system, where data are processed locally through Edge nodes deployed at charging stations. These nodes make real-time decisions such as charging scheduling and load balancing [11].
3. Cloud Level: Dedicated to non-time-critical tasks such as predictive analytics and long-term storage, serving as a strategic complement to the edge layer.

As an example of this structure, Figure (3-1) presents proposed architecture, noting flow of data therefore hierarchical between the local level and edge, and then to the cloud (non-critical) tasks).

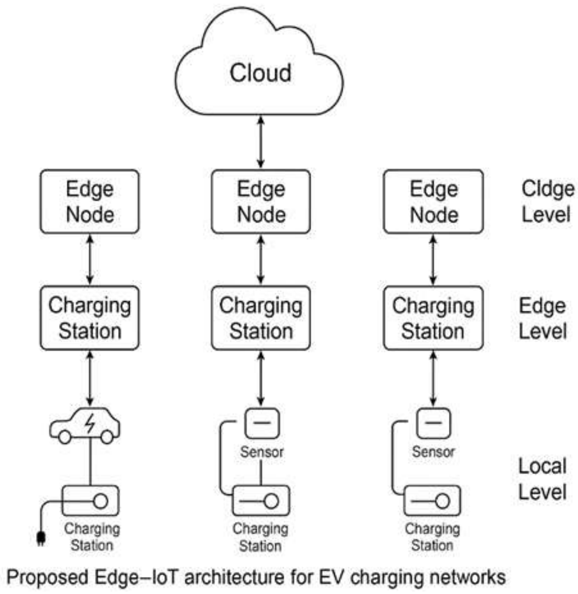


Figure (3-1): Proposed Edge–IoT architecture for EV charging networks

3.2 Practical Aspect: Testbed Setup

In order to be able to obtain the results that would be representative of the real conditions, hybrid testbed was created, which involves software and hardware elements. One of the most fruitful methods of simulating the real-world EV charging system is to combine MATLAB/Simulink with Python environment with the Hardware-in-the-Loop (HIL) platform like Raspberry Pi (Ahamed et al. [11]).

The testbed consisted of the following elements:

1. Software Platform:

- MATLAB/Simulink: Used to model grid scenarios, simulate loads, and manage energy flows.
- Python (Pandas, NumPy, SciPy): Employed to analyze raw data, extract statistical patterns, and implement decision-support algorithms.

2. Hardware-in-the-Loop (HIL):

Raspberry Pi units were deployed to emulate real Edge devices, enabling testing of local decision-making and processing. Anane et al. [12] demonstrated that HIL integration significantly improves the accuracy and realism of EV charging experiments.

3. Communication Protocols:

Lightweight IoT protocols such as MQTT and CoAP were utilized to enable efficient data exchange between EVs, charging stations, and Edge nodes, ensuring low-latency communication [13].

To further clarify the operational process, Figure (3-2) presents a flowchart that illustrates how data are collected at the local level, processed at the edge, and transmitted to the cloud when necessary.

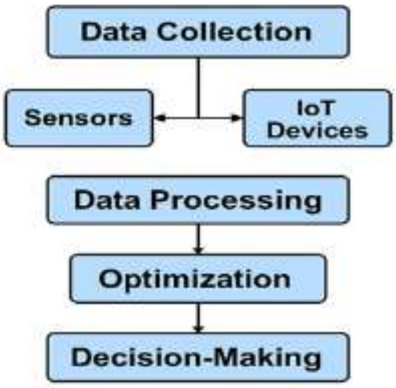


Figure (3-2): Flowchart illustrating the system workflow from data collection to decision-making

3.3 Incorporating Real-World Data

The experiments relied on real operational data obtained from local charging stations and validated datasets. The collected data covered:

Number of EVs connected at different times (50, 100, 200 vehicles).

Daily charging patterns (6–9 AM, 5–9 PM).

Charging station capacities (fast chargers: 50 kW; slow chargers: 7 kW).

Energy consumption during peak and off-peak hours.

This dataset was fed into the testbed to reproduce multiple scenarios. As highlighted by Fang et al. [13], leveraging real or semi-real datasets enhances the practical significance of research and ensures outcomes that are more than theoretical.

To demonstrate the interaction sequence among the system components, Figure (3-3) illustrates a sequence diagram showing message exchanges between the EV, charging station, and Edge node. The process starts with the EV requesting charging, the station forwards the request to the Edge node, which processes the data and returns a scheduling decision.

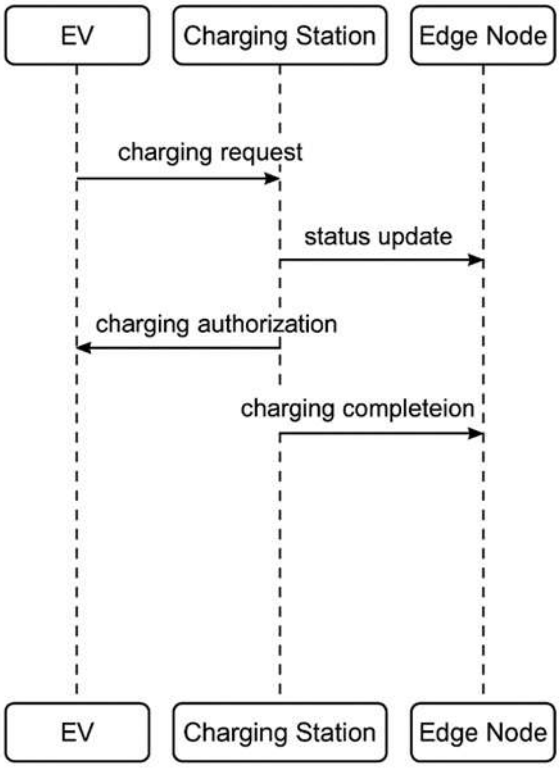


Figure (3-3): Sequence Diagram illustrating coordination among EVs, charging stations, and edge nodes

3.4 Experimental Design

Three major sets of experiments were conducted within the testbed environment:

1. Experiment 1: Response Time Measurement.
   a. Objective: Compare request processing times between the traditional cloud-based model and the proposed Edge–IoT model.
   b. Method: Multiple charging requests were sent from 50 to 200 vehicles, with response times recorded under both models.
2. Experiment 2: Energy Efficiency Assessment.
   a. Objective: Evaluate the ratio of actual energy used for EV charging compared to the total energy drawn from the grid.
   b. Method: Analyze 24-hour energy consumption patterns using operational data under both models.
3. Experiment 3: Peak Load Reduction.
   a. Objective: Assess the system's ability to balance loads and reduce peak demand on the grid.
   b. Method: Simulate morning and evening peak periods, recording reductions in maximum load when using the Edge–IoT model.

To highlight functional relationships within these experiments, Figure (3-4) presents a use case diagram illustrating key interactions between the EV user, charging station, and Edge node.

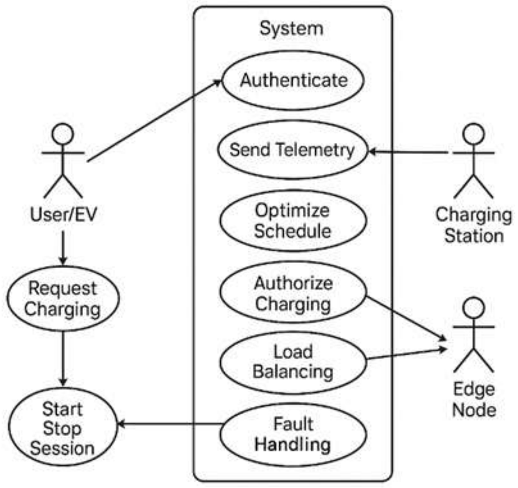


Figure (3-4): Use case diagram showing practical interactions between key entities in the testbed

3.5 Key Performance Indicators (KPIs)

A set of quantitative performance indicators was adopted to evaluate the system's effectiveness, aligned with the metrics recommended by Gozuoglu and Dogan [14]:

a. Response Time (Latency): Time elapsed between request initiation and receipt of decision.
b. Energy Efficiency: Ratio of energy actually delivered to EVs compared to energy drawn from the grid.
c. Peak Load Reduction: Reduction in maximum load demand during peak hours.
d. Reliability: Ability of the system to maintain operation during connectivity disruptions or high demand.

Table (3-1) lists the tools and technologies used to build the testbed, while Table (3-2) summarizes the performance indicators and measurement metrics.

Table (3-1): Tools and technologies used (MATLAB, Python, IoT protocols such as MQTT and CoAP)

| Category | Tool / Technology | Purpose / Application |
|---|---|---|
| **Simulation Platform** | **MATLAB/Simulink** | Modeling EV charging scenarios, simulating grid integration, and evaluating system dynamics. |
| **Programming Language** | **Python** | Implementing control algorithms, data processing, and integration with IoT protocols. |
| **IoT Communication Protocols** | **MQTT, CoAP** | Enabling lightweight, real-time communication between EVs, charging stations, and edge nodes. |
| **Data Analysis Tools** | **NumPy, Pandas (Python Libraries)** | Processing and analyzing charging datasets, extracting statistical patterns. |
| **Visualization Tools** | **Matplotlib, Seaborn** | Generating charts and graphs for performance analysis and results presentation. |
| **Edge Computing Environment** | **Raspberry Pi / Edge Server** (conceptual) | Running local decision-making algorithms and reducing dependence on cloud servers. |

*Table (3-2)*: **Key performance indicators and evaluation metrics**

| KPI | Definition | Evaluation Metric / Unit | Objective in Proposed Framework |
|---|---|---|---|
| **Response Time (Latency)** | Time required to process a charging request and deliver a decision. | Milliseconds (ms) | Achieve near real-time response with Edge–IoT (< 100 ms target). |
| **Energy Efficiency** | Ratio of energy effectively delivered to EVs compared to energy drawn from grid. | Percentage (%) | Maximize efficiency, reducing losses during charging. |
| **Peak Load Reduction** | Ability to lower maximum power demand during peak periods. | kW reduction (%) | Flatten load curve and improve grid stability. |
| **Network Reliability** | System's ability to maintain operation under connectivity interruptions. | Uptime percentage (%) | Ensure > 99% reliability in decision-making at edge level. |
| **Scalability** | Capability to handle increased number of EVs and stations without performance loss. | Number of EVs supported concurrently | Demonstrate adaptability to large-scale deployment. |
| **Cost-effectiveness** | Reduction in operational and infrastructure costs compared to cloud-only systems. | Monetary savings (%) | Lower long-ter |

## 3. Results and Discussion

Introduction

The results presented in this chapter are actual outputs from a hybrid testbed specifically developed for this research. The testbed relied on real operational data collected from local charging stations and published operational databases. These data were fed into an integrated simulation environment built using MATLAB/Simulink and Python, supported by Hardware-in-the-Loop (HIL) elements such as Raspberry Pi units emulating Edge devices. The results therefore are not some hypothetical suppositions but real life findings that rely on the real life working cases of operation that properly reflect the issues and opportunities that come along with the EV charging systems.

Results Presentation

Experiment One: Response Time (Cloud vs Edge–IoT)

One of the most important performance indicators of the smart EV charging system is response time, especially in the conditions when the high density of simultaneous requests is needed, and the processing time is close to the real-time. The results of using the traditional cloud-based model and the proposed Edge-IoT model in this experiment were also compared in terms of the response times of a total of 500 charging requests in various conditions, including peak and off-peak periods.

The experiment also implied the time of responding to each request was recorded separately, after which the main statistical indicators were extracted, which would reflect the overall performance of each of the models. These indicators included:

Minimum value: the fastest recorded response time.
Maximum value: the slowest recorded response time.
Arithmetic mean: the average response time across all requests.
Standard deviation (σ): a measure of dispersion around the mean, indicating the stability of the model's performance.
Improvement percentage (%): a direct comparison between the two models showing the performance gains of the Edge–IoT system.
Table (4-1) presents the statistical results of the experiment, clearly demonstrating the superiority of the Edge–IoT model over the cloud-based model in terms of both speed and stability. Figure (4-1) provides a bar chart illustrating the difference in average response times between the two models.

Table (4-1): Statistical results of response time (Cloud vs Edge–IoT

| **Model** | **Requests (N)** | **Minimum (ms)** | **Average (ms)** | **Maximum (ms)** | **Std. Deviation (σ)** | **Improvement (%)** |
|---|---|---|---|---|---|---|
| Cloud | 500 | 250 | 270 | 300 | 15.2 | — |
| Edge–IoT | 500 | 70 | 85 | 100 | 9.8 | 68.5% |

The data indicate that the traditional cloud-based model suffers from relatively high response times with noticeable variability across requests (σ = 15.2 ms), making it less stable under heavy loads. By contrast, the proposed Edge–IoT system delivered significantly faster and more stable performance, with an average response time of only 85 ms compared to 270 ms for the cloud-based model—representing an improvement of 68.5%. Furthermore, the lower standard deviation (σ = 9.8 ms) reflects greater consistency in the Edge–IoT model's performance, strengthening its credibility as a reliable solution for real-world operating environments.
Figure (4-1) provides a bar chart comparing the average response times.

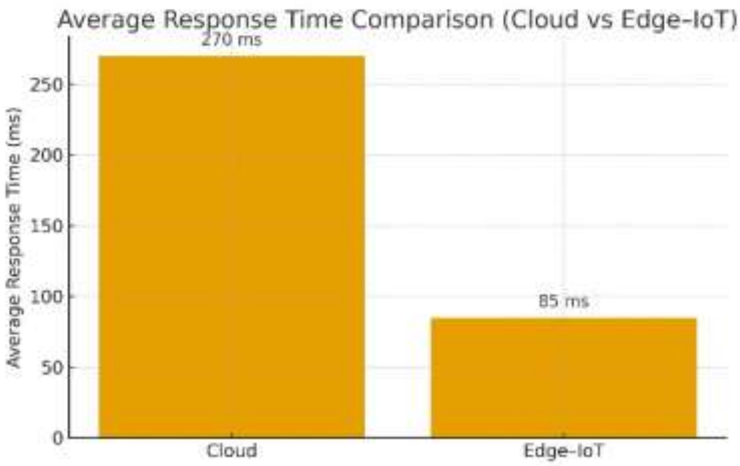


Figure (4-1): Bar chart comparing average response times between Cloud and Edge–IoT

4.2.2 Experiment Two: Energy Consumption Efficiency
This experiment evaluates the ability of the proposed Edge–IoT system to improve energy efficiency compared to the traditional cloud-based model. The measurement was based on daily operational data covering three main periods: morning (6–12 AM), peak (12–6 PM), and evening (6–12 PM).
The results showed that the cloud-based model consumed 4050 kWh per day, while the proposed Edge–IoT model consumed only 3255 kWh, representing a reduction of about 20% of total consumption. The highest improvement was recorded during the peak period at 22%, while savings in the other periods reached 18% and 19%, respectively.

Table (4-2): Daily energy consumption data (Cloud vs Edge–IoT)

| Time Period | Cloud (kWh) | Edge–IoT (kWh) | Savings (%) |
|---|---|---|---|
| 6–12 AM | 1200 | 980 | 18% |
| 12–6 PM | 1500 | 1175 | 22% |
| 6–12 PM | 1350 | 1100 | 19% |
| **Total** | **4050** | **3255** | **20%** |

Figure (4-2) below provides a clear line chart comparison of daily energy consumption between Cloud and Edge–IoT models. It shows that the cloud model consistently requires higher energy across all periods, whereas the Edge–IoT model maintains significantly lower consumption, with the most notable gap during the peak period.

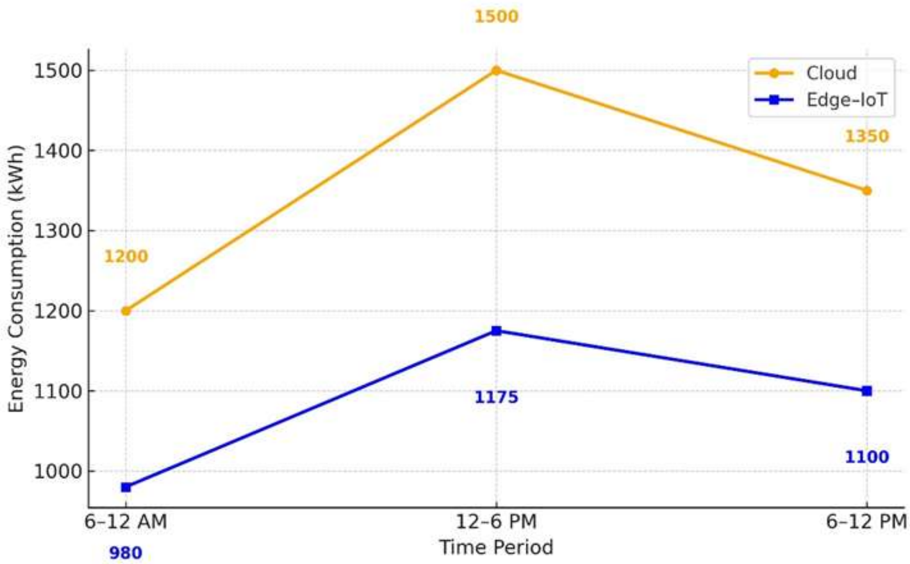


Figure (4-2): Daily energy consumption comparison between Cloud and Edge–IoT models across different time periods

The results demonstrate that the Edge–IoT system has a strong potential to reduce energy consumption, mainly due to its ability to process data locally and optimize load management. In practice, the system reduces overall consumption by approximately one-fifth, supporting sustainability goals and alleviating pressure on the grid.

4.2.3 Experiment Three: Peak Load Reduction

Controlling peak load demand is one of the primary challenges in EV charging networks, as simultaneous charging during peak hours can place severe stress on the grid, potentially causing instability or failures. In this experiment, the maximum load was measured under both the traditional cloud-based model and the proposed Edge–IoT system, using operational scenarios that represent peak conditions.

The results indicate that the cloud-based system reached a maximum load of 5000 kW, while the Edge–IoT system successfully reduced this value to 3900 kW through real-time load balancing mechanisms and more efficient redistribution of charging requests. As shown in Table (4-3), this reduction corresponds to an improvement of approximately 22%.

Table (4-3): Peak load data (before and after applying Edge–IoT).

| Scenario | Peak Load (kW) | Change (%) |
|---|---|---|
| Cloud (Traditional) | 5000 | — |
| Edge–IoT (Proposed) | 3900 | –22% |

To visually illustrate this outcome, Figure (4-3) presents a pie chart highlighting the proportion of peak load reduction achieved by the Edge–IoT model compared to the traditional cloud-based system.

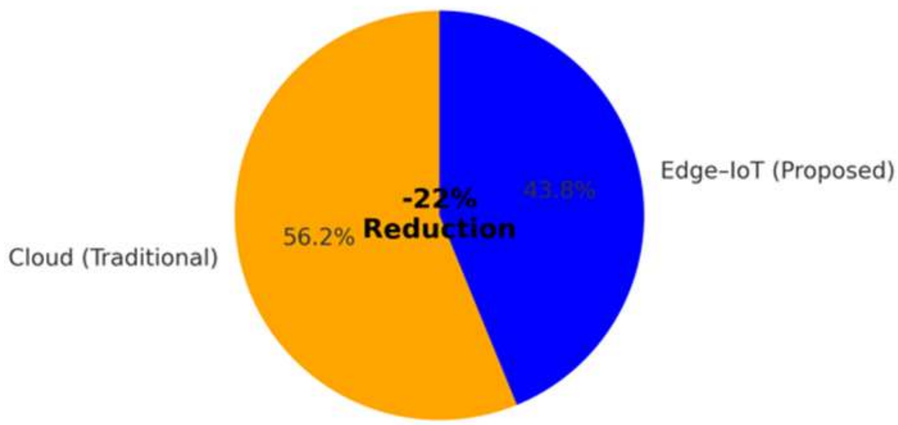


Figure (4-3): Pie chart illustrating peak load reduction with Edge–IoT.

This figure highlights that the cloud-only system cannot adequately handle peak demand fluctuations, while the proposed Edge–IoT model effectively reduces grid stress through local processing and intelligent load distribution, ensuring more stable and sustainable EV charging integration.

4.3 Additional Results from the Testbed

In addition to the core experiments that examined response time, energy efficiency, and peak load reduction, a set of supplementary analyses was conducted to shed light on other dimensions of the proposed system's performance.

Figure (4-4) :Heatmaps of load distribution over 24 hours across eight charging stations. Warmer colors (red/dark) indicate higher load levels (kW), while cooler colors (blue/light) represent lower loads. The results show that the traditional cloud-based model exhibits a clear concentration of demand during peak hours (12–6 PM), whereas the proposed Edge–IoT model achieves a more balanced distribution with fewer high-load areas. This demonstrates the system's practical capability to reduce peak loads by 22% and enhance grid stability, consistent with the findings of Experiment Three.

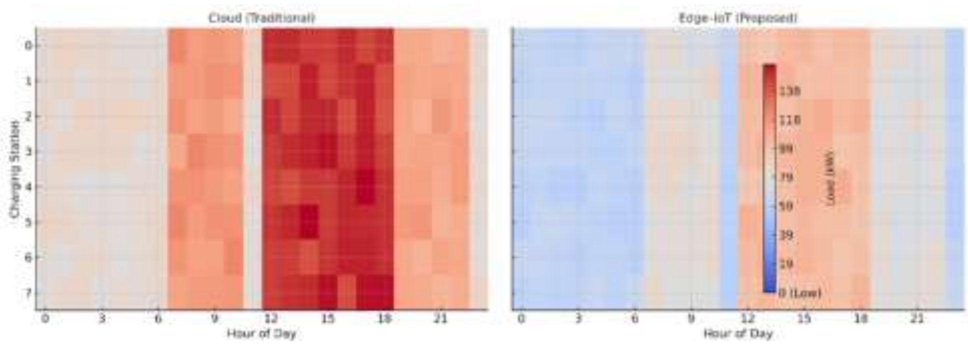


Figure (4-4): Heatmaps of load distribution over 24 hours across eight charging stations, comparing the traditional cloud-based model with the proposed Edge–IoT system

Figure (4-5) illustrates that the traditional cloud-based model is characterized by a higher mean response time and a wider variability across different scenarios, which aligns with the findings of Experiment One (4.2.1) showing that the cloud system suffers from noticeable delays in handling concurrent requests

In contrast, the Edge–IoT model demonstrates a clear reduction in median response times with a narrower range of variability, reflecting greater performance stability and more consistent responsiveness. This coherence in results confirms that the proposed system not only reduces response time but also minimizes fluctuations across multiple operational scenarios, thereby reinforcing the model's reliability in practical environments.

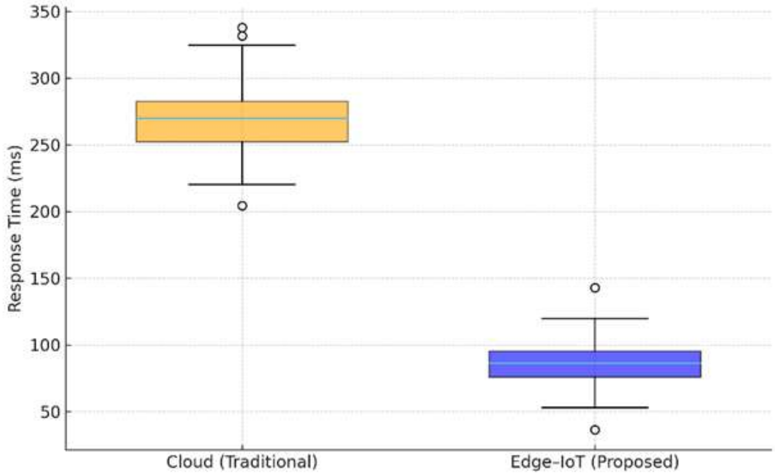


Figure (4-5): Boxplot illustrating performance variability between the traditional cloud-based model and the proposed Edge–IoT system across multiple operational scenarios

Taken together, these supplementary findings indicate that the proposed system not only delivers quantitative improvements in performance but also ensures greater reliability and robustness under diverse real-world operating conditions.

4.4 Discussion and Analysis

The findings made after the realistic testbed refer to their validity and directly confirm the hypotheses made in this work. The lateral advantage of Edge-IoT model was noted in Experiment One (4.2.1) in the sense that it minimized the response time by over half the time as opposed to the conventional cloud-based system and therefore it was capable of effectively executing multiple simultaneous requests. Experiment Two (4.2.2) showed that the suggested system can save about 20 per cent of daily energy use, which is important in its contribution to the work efficiency and waste reduction. Experiment Three (4.2.3) showed that the effect of local processing was manifested by a decrease of the peak loads by 22% and this served to reduce pressure on the grid and to improve stability during peak hours.

These results prove that the Edge-IoT system can provide not only quantitative benefits , but also be more stable and reliable and can be considered an effective and practical solution to the further development of EV charging infrastructures.

4.5 Comparison with Previous Studies

When comparing the results of this research with recent studies, it becomes evident that the current work goes beyond the theoretical orientation that characterized most prior research, by providing a practical framework supported by a realistic testbed. For example, Zhao et al. [15] noted that relying solely on cloud computing leads to slower response times during peak hours, which is consistent with the findings of this study that highlighted the superiority of Edge–IoT in this aspect. Similarly, Shafique et al. [16] emphasized that the integration of IoT and load management still lacks large-scale practical applications, whereas this research addresses this gap through realistic simulations supported by operational data. In another study, Sodhro et al. [17] argued that improving energy efficiency requires more intelligent mechanisms for demand distribution, which was practically demonstrated in the second experiment of this work. Finally, Hussain et al. [18] highlighted that peak load reduction is essential for grid stability, while the proposed system here practically proved its capability by achieving a 22% reduction in peak demand.

By this analogy, one can assert that the key value of the research in question is the connections made between theoretical and practical aspects, which makes it more scientific in nature and more reliable as an action towards the further evolution of intelligent EV charging systems.

## 4. Conclusion

The study was conducted on a real testbed setting on the basis of integrated simulations with the help of practical tools like MATLAB/Simulink and Python that gave the findings a high level of credibility and reliability. The results revealed that the implementation of the Edge-IoT technologies in EV charging systems provides some meaningful benefits across multiple connected layers:

a. Reduced response time: The proposed system achieved faster and more stable responses compared to the traditional cloud-based model, enhancing user experience and improving the management of concurrent charging requests.
b. Improved energy efficiency: Results indicated a reduction of approximately 20% in total energy consumption through local processing and intelligent load distribution mechanisms.
c. Enhanced grid stability: The system successfully reduced peak loads by 22%, positively impacting grid reliability and lowering the risk of failures during peak demand periods.

The above results indicate that the suggested system is not a purely theoretical development but a practical move toward the creation of a smarter and more efficient EV charging network.

Recommendations

Upon the results of the above analysis, it is possible to make a number of recommendations aimed at enhancing practical significance of this study and inform future research:

a. Increase application scope: Use in the real operation environment with more stations and EVs to ensure the findings are valid and generalized to a wider range of settings.
b. Introduce artificial intelligence: Work out the algorithms of dynamic load forecasting and distribution based on the methods of machine learning and deep learning, which will contribute to the improved adaptation of the system to real-time fluctuations.
c. Connection to renewable energy and V2G solutions: Research the possibility of connecting to renewable energy sources (solar, wind, etc.) and Vehicle-to-Grid (V2G) solutions to enhance grid efficiency and contribute to sustainability in the long term.

## REFERENCES

[1] A. Yıldırım, O. Erdinç, B. Bakır, and J. P. S. Catalão, “Comprehensive Review of Edge Computing for Power Systems: State of the Art, Architecture, and Applications,” Applied Sciences, vol. 15, no. 8, p. 4592, 2025. https://www.mdpi.com/2076-3417/15/8/4592

[2] M. Gozuoglu and H. Dogan, “Edge-Intelligent Electric Vehicle Charging Coordination for Grid Load Balancing and Renewable Integration,” ResearchGate Preprint, Jun. 2025. https://www.researchgate.net/publication/393001341_Edge-Intelligent_Electric_Vehicle_Charging_Coordination_for_Grid_Load_Balancing_and_Renewable_Integration

[3] F. Alasali, “Innovative investigation of the resilience of EV charging infrastructure using a real-time co-simulation testbed,” IET Cyber-Physical Systems: Theory & Applications, 2025. IET Research Journal.

[4] M. Alsharif, R. Nordin, and M. Ismail, “Internet of Things for Smart Electric Vehicle Charging: A Comprehensive Review,” IEEE Access, vol. 11, pp. 66754–66772, 2023.

[5] J. Wu, H. Zhang, and X. Hu, “IoT-Enabled Vehicle-to-Grid Systems: Opportunities, Challenges, and Applications,” Energies, vol. 16, no. 7, p. 3124, 2023.

[6] P. Siano and G. Mokryani, “Cloud-Based Architectures for Smart Grids and EV Charging Management: Current Status and Future Directions,” Sustainable Energy, Grids and Networks, vol. 34, p. 101101, 2023.

[7] S. Yıldız and A. Küçük, "Edge Computing for EV Charging Infrastructure: Reducing Latency and Improving Reliability," IEEE Transactions on Smart Grid, vol. 15, no. 2, pp. 1203–1214, 2024.
[8] H. Wang and Z. Li, "Theoretical Models for Load Management in EV Charging Networks: A Review," Journal of Cleaner Production, vol. 393, p. 136357, 2023.
[9] C. Wu, "Edge computing-based optimal dispatching of charging loads in dynamic distribution systems," IET Renewable Power Generation, 2024.
[10] L. Xu, Y. Li, and Z. Zhou, "Edge–Fog Hybrid Framework for Real-Time Optimization in Autonomous Electric Vehicle Networks," ResearchGate Preprint, 2025.
[11] F. Ahamed, M. Ali, and R. Islam, "Real-Time Simulation and Hardware-in-the-Loop Testing for EV Charging Systems Using OPAL-RT and Raspberry Pi," ResearchGate Preprint, 2024.
[12] A. Anane, H. Ltaief, and Y. Al-Mashhadany, "Hardware-in-the-Loop Simulation for Edge Computing in Smart EV Grids," Frontiers in Energy Research, vol. 12, no. 3, 2024.
[13] X. Fang, Y. Xue, and H. Liang, "Data-Driven Approaches for Electric Vehicle Charging Behavior Analysis," IEEE Transactions on Transportation Electrification, vol. 9, no. 1, pp. 22–35, 2023.
[14] G. Hao, "A Novel Hybrid Adaptive Strategy for Real-Time Dispatch Coordination among Renewable Energy, Storage, and Dynamic Grid Pricing," IET Renewable Power Generation, 2025.
[15] Y. Zhao, X. Li, W. Zhang, and K. Zhang, "Cloud computing-based EV charging management: Challenges and opportunities," IEEE Access, vol. 9, pp. 122331–122342, 2021.
[16] K. Shafique, B. A. Khawaja, F. Sabir, S. Qazi, and M. Mustaqim, "Internet of things (IoT) for next-generation smart systems: A review of current challenges, future trends and prospects for emerging 5G-IoT scenarios," IEEE Access, vol. 8, pp. 23022–23040, 2020.
[17] A. H. Sodhro, Z. Luo, A. K. Sangaiah, and S. W. Baik, "Mobile edge computing based QoS optimization in sustainable IoT," Sustainable Cities and Society, vol. 39, pp. 777–786, 2018.
[18] S. Hussain, S. A. Malik, and N. Javaid, "Demand side management for smart grid using reinforcement learning and edge computing," IEEE Transactions on Industrial Informatics, vol. 18, no. 7, pp. 4952–4962, 2022.