Artificial Intelligence and Machine Learning in Engineering Applications

Himanshu Gupta, Sanjeev Tayal, Parag Jain, Abhay Bhatia, Lokesh Kumar

***Abstract:** Today, AI and ML are used in almost all domains, from engineering to medicine. AI is transforming the way researchers/engineers used to solve problems. AI is making processes more efficient, flexible and fast. AI needs data to make decisions. Basically, it captures the patterns in the data. Engineers today is using AI tools to address problems across almost every engineering domain, including manufacturing, urban planning, and transportation. The objective of this study is to explore AI applications across various engineering fields, with particular attention to electric vehicle (EV) charging. In this study, we used a dataset from a publicly available repository (Kaggle) in CSV format, containing data from 3,395 charging sessions by 85 EV users at 105 stations across 25 workplaces. We performed an exploratory analysis of this dataset and identified several interesting trends, including average and peak energy consumption, peak charging time, and the busiest charging stations. Some findings include that 5 kWh was consumed in most sessions, though a few drew noticeably more energy. From the analysis, it is found that on Thursdays, charging activities are more than usual, roughly around 11 a.m. This may be due to the regular office schedules. It is also observed that type 3 charging stations were used most frequently, and a large share of energy was consumed from these stations. These insights provide a practical understanding of how people charge their EVs at the workplace. By understanding this challenging pattern, organisations can schedule their charging facilities more effectively. Further organizations can make strategy to motivate their employees to charge their EV vehicles during non-peak hours.*

***Keywords:** Artificial Intelligence (AI), Machine Learning (ML), AI Applications, Electric Vehicle (EV) Charging, AI in Engineering, Decision Making.*

Nomenclature:
AI: Artificial Intelligence
ML: Machine Learning
EV: Electric Vehicle
EDA: Exploratory Data Analysis

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I. INTRODUCTION

Artificial Intelligence (AI) and Machine Learning (ML) [1][2][3] technologies are widely used in engineering applications; in almost all engineering domains, researchers use machine learning and AI for prediction or intelligent decision-making. AI and ML help researchers find hidden patterns in the data. As computing power grows and large datasets are made publicly available, the use of AI across cross-domain applications has increased. Further modern techniques, such as attention mechanisms and transformers, have also boosted the use of AI for tackling complex engineering problems.

A. Applications of AI and ML in Engineering

This section discusses the various use cases of AI & ML in different engineering branches:

Mechanical engineers make great use of AI and ML for predictive maintenance and fault detection. For example, if we take a sensor dataset from CNC machines or robotic arms that has columns such as vibration level or temperature. Classification models or regression models can be applied to the obtained dataset to predict failures before they occur. This can help reduce the downtime and maintenance costs [4]. AI-enabled systems can identify defective parts with high accuracy and maintain consistent production.

Other engineering branches also have application of AI in their domain, civil and structural engineers using AI to monitor bridges, roads and buildings. For AI to make predictions or perform classification, data is needed. For this, different sensors can be deployed on bridges to record parameters such as strain, displacement, and vibration. Once we have the data, we can use ML models such as gradient boosting and SVMs to identify unusual patterns. Alerts can be triggered if some parameters exceed limits, so problems can be fixed before they become serious. Some civil engineering projects also use genetic algorithms to optimise bridge designs or innovative city layouts [5].

AI is also widely applied in the electrical and power systems. Smart grids balance supply and demand, integrate solar/wind energy, and reduce losses [6]. So basically, AI models rely on data. If we have data, we can use AI models to find patterns and make predictions. LSTM is a popular model that works well for time-series data; this company can forecast energy consumption. AI helps EV batteries, too. By optimising charging schedules, peak hours' load can be minimised, improving overall efficiency.

AI is used in transportation to control public transportation and traffic. Models are fed data from GPS, cameras, and Internet-of-Things sensors to forecast traffic and recommend routes.

Autonomous cars process inputs from lidar_data, camera_frames, and radar_signals using deep learning, sensor fusion, and reinforcement learning. They converse with other cars and make driving decisions.

AI forecasts emissions, water levels, and air quality to support sustainability and environmental protection. ML models identify pollution and maximise wastewater treatment using air quality and wastewater data obtained from various sensors. These applications increase the sustainability and efficiency of systems.

B. Workplace EV Charging & Data Analysis

This study is divided into two parts: the first discusses the use of AI in various engineering domains, and the second focuses on EV charging etiquette. Workplace EV chargers can get messy. Many employees share a few stations, and some ignore rules, which causes long waits. To analyse this, we have collected a public dataset station_data_dataverse.csv from a public repository (Kaggle). station_data has 3,395 sessions from 85 users at 105 chargers in 25 workplaces. This CSV file includes columns user_id, station_id, start_time, end_time, and kWh_used. We have conducted exploratory data analysis on this CSV file and identified multiple insights, which are discussed in the results and discussion section of the paper.

C. Significance of the Study

In this work, the first part explores the applications of AI across various engineering domains, followed by an exploratory data analysis of a publicly available dataset of workplace EV charging stations. This analysis helps identify patterns in employees' EV charging habits. This analysis has shown which stations get crowded, when etiquette is ignored, and, using these insights, the workplace can improve the scheduling of shared resources. With proper scheduling, predictions, and rules, EV charging becomes faster, more reliable, and easier to manage. The detailed analysis of the study is discussed in the results section of the paper.

II. LITERATURE REVIEW

The growth of Artificial Intelligence (AI) and Machine Learning (ML) has changed many engineering fields in the last few years [7]. This power is demonstrated by one AI framework that has been successfully used across areas such as fault detection, medical systems, oil, and space travel [8]. This shows AI can really help solve problems across different job domains.

In structural engineering, researchers also find various applications of AI. An extensive review of about 4,000 papers by [9] concluded that AI and ML are widely used in areas such as predicting material properties, engineering for earthquakes, wind, and fire, and assessing the health of structures. In their extensive review, the authors noted that machine learning and deep learning achieve faster, more accurate results than older methods. This encourages them to explore AI further in this field. Similarly, researchers have found significant applications of AI in the oil and gas sector. Using AI to analyse data more effectively, identify risks, and plan needed repairs can be done more accurately and efficiently. This leads to better work, more trust, and safer exploration [10].

It is worth noting that AI is not just for one field. Another study by [11] explored its uses in physics, materials engineering, and medicine. They stressed that AI can help make decisions faster, predict things, and also automate tasks. Also, a study of over 1,200 papers by [12] in soil engineering showed that Artificial Neural Networks are widely used in the field. ANNs are helping in areas such as foundation design, tunnel construction, and slope stability assessment. ANNs handle uncertainty better, which helps reduce cutting costs and make buildings safer.

But even with all its merits, the Use of AI and ML in materials and structures engineering has been slow. This problem arises because materials data is often messy and doesn't align [13]. To more quickly adapt AI in this domain, the authors suggested that AI be taught in engineering schools. Beyond traditional engineering, AI has quietly become part of our daily routines. We use it when we search the web, unlock our phones with facial recognition, or let our email apps filter out spam [14].

In civil engineering, researchers have been exploring how big data and deep learning can improve structural maintenance, management, and design in large construction projects [5]. However, there are still some real challenges, such as a study on using AI for disaster planning, innovative design, and structural inspection [15], which discussed techniques such as detecting damage from camera images and using machine learning to spot potential issues. A primary concern is that there aren't enough reliable ways to validate these results regularly.

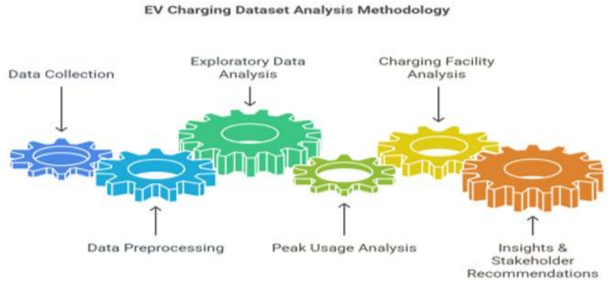
In fire engineering, various machine learning models, such as SVMs, decision trees, and KNNs, as well as deep learning, are being extensively used to study how materials perform and how fires behave [16]. This work shows that AI can improve fire safety checks. Machine learning is widely used in structural engineering because it can track complex patterns. A separate study demonstrated how machine learning is used to predict material properties, check fire resistance, monitor health, and conduct structural analysis. It focused on using data sets, Python code, and machine learning tools to make it easier for engineers to adopt AI [17].

AI is also being used to enhance Electric Vehicle (EV) charging spots. Research on shared EV charging stations in the US examined incentives and other factors to encourage more efficient charging habits [18]. It found that changing prices, along with agreed social rules, significantly influence whether people follow those rules. Additionally, other research explored various AI models, including KNN, Random Forest, SVM, and LSTM, for innovative grid management of EV charging [19]. It is observed that the LSTM model helped stabilise voltage, reduce energy loss, and manage charging to prevent overloading the power grid.

Reliability in EV charging is likewise essential [20]. analysed 12,720 EV stations across 651 regions in the US and used ML to categorise consumer opinions. Private stations don't always perform better than public ones, indicating that public EV infrastructure needs improvement [21]. showed that reliability is a primary barrier for EV adoption. This research suggests that ML can be highly beneficial for analysing largescale EV data and planning advanced charging networks.

III. METHODOLOGY

This study is divided into two main sections. The first discusses the use of machine learning and artificial intelligence in different engineering fields, while the second part concentrates on the exploratory analysis of the public EV charging dataset. We conducted the exploratory data analysis by following the steps depicted in Figure 1. The sections that follow provide greater detail on each of these steps.



[Fig.1: Methodology]

A. Data Collection

We used the station_data_dataverse.csv dataset, available on Kaggle. It includes thorough logs of EV charging sessions. Among the many columns in the CSV file are sessionId, kWh Total, dollars, created, ended, startTime, endTime, charge Time Hrs, weekday, platform, distance, manager Vehicle, facility Type, daily usage flags (Mon-Sun), and reported Zip. We used various preprocessing techniques and exploratory analysis on the clean data to uncover insights.

B. Data Preprocessing

A good analysis is only possible on good data. So before performing the exploratory data analysis, the dataset went through the following pre-processing steps: -

i. Handling Missing Values:

The dataset was checked for missing values, and the column's mean was used to impute them.

ii. Data Type Conversion:

To accurately calculate charging durations, the start Time and end Time fields in the CSV file were converted to datetime objects. To confirm data accuracy, the computed time difference was cross-checked with the charge Time Hrs column. To perform group-based analyses, the categorical columns in the CSV file, such as weekday and facility Type, were also converted to categorical data types.

iii. Feature Engineering:

Some new features (columns) are derived from the existing fields of the CSV file:

- A new column, Day of Week, is derived from the weekday field to study charging trends across days.
- The dollars column in the dataset was cross-checked with kWh Total to ensure pricing consistency.
- A new field charging Rate was also added to represent the average power consumption rate per charging session.

C. Exploratory Data Analysis (EDA)

To understand charging behaviour and track any irregularities, we carried out a thorough data analysis:

i. *Descriptive Statistics:* various descriptive parameters, such as mean, median, min, max, and standard deviation, are computed for multiple columns of the dataset.

ii. *Visualisation Techniques:* To visualise trends clearly, various plots such as histograms, boxplots, count plots, scatterplots, and heat maps are used.

D. Peak Usage Analysis

To identify busiest periods:

i. *Peak Charging Day:* The dataset is analysed to find out the busiest day of the week.

ii. *Peak Charging Hour:* Exploratory analysis is also performed to find the peak charging hour.

iii. *Platform and Location Analysis:* Analysis is also carried out to check the most preferred platform and location by the employees for EV charging.

E. Charging Facility Analysis

We also analyzed the facility level to gain more detailed insights. For example:

i. *Session Count by Facility Type:* We analysed how many charging sessions occurred for each facility type to identify which charger types were used the most.

ii. *Energy Consumption by Facility Type:* We calculated the total energy consumed (in kWh) for each facility type and used bar charts to compare and visualise how much energy each category utilised.

iii. *Daily Usage Patterns:* To understand how charging activity varied throughout the week, we examined the columns representing Monday to Sunday and studied the daily trends and occupancy levels.

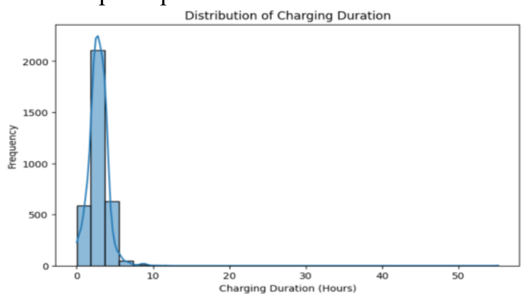
IV. RESULTS AND ANALYSIS

This section discusses the results of the exploratory analysis carried out on the EV charging dataset. Results are presented in three main categories, namely descriptive statistics, peak usage trends, and facility-specific observations. The following sections discuss each category in detail: -

A. Descriptive Statistics

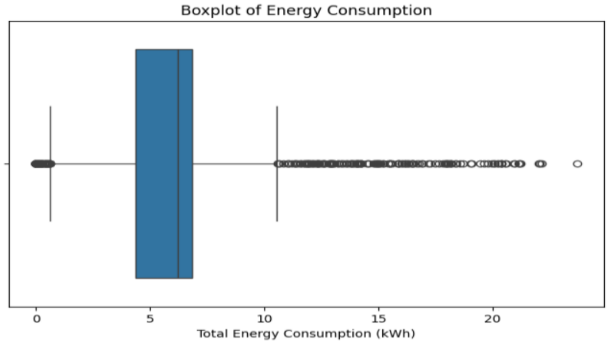
The statistical analysis of the dataset provides key insights into charging session characteristics:

i. As per the analysis, the maximum recorded energy consumption is 23.68 kWh, while the average consumption per session is 5.81 kWh.



[Fig.2: Distribution of Charging Duration]

ii. The Average charging time is 2.84 hours. However, the most extended recorded session lasted 55.23 hours, suggesting a possible outlier.

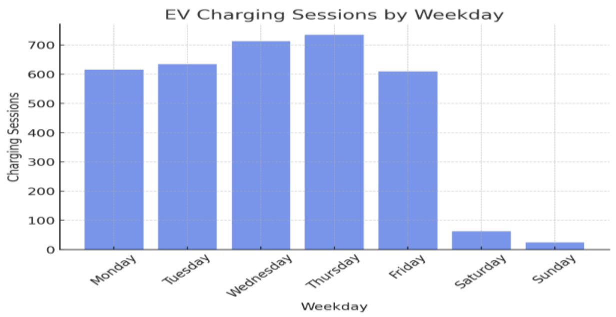


[Fig.3: Boxplot of Energy Consumption]

If we observe closely, the charging durations plot is right-skewed. This suggests that some sessions are significantly longer than others, while most are relatively shorter. The analysis shows that an average of 5 kWh of energy is consumed per session, but some sessions consume more than 20 kWh, which may be due to the larger battery. Some outliers suggest that a small percentage of users have used a disproportionately high amount of energy.

B. Peak Usage Trends

To better understand how charging demand changes over time, we also analysed how sessions were distributed across different weekdays and hours of the day. The key findings from this analysis are as follows:

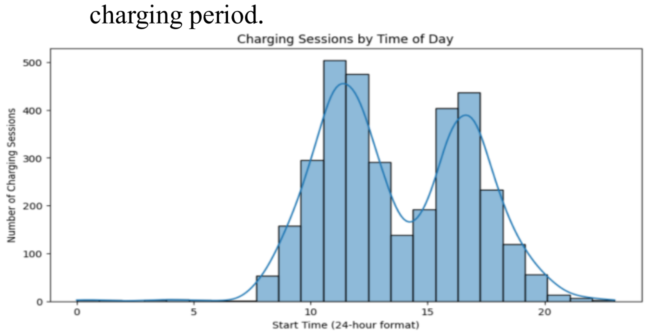


[Fig.4: EV Charging Sessions by Weekday]

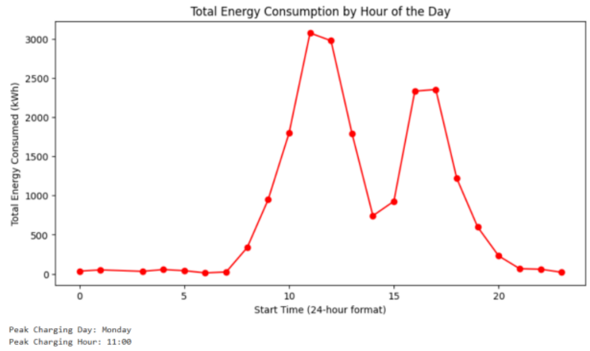
i. *Busiest Day:* Thursday saw the highest number of charging sessions, with 735 in total. This shows that most users prefer charging their vehicles around midweek (see Figure 4).

ii. *Quietest Day:* Sunday, with just 24 sessions, had the lowest activity. This drop clearly points to less charging on weekends.

iii. *Peak Energy Use:* Energy demand also peaked on Thursday, with total consumption reaching 4,235.13 kWh. This again highlights that midweek is the busiest charging period.



[Fig.5: Charging Sessions by Time of Day]

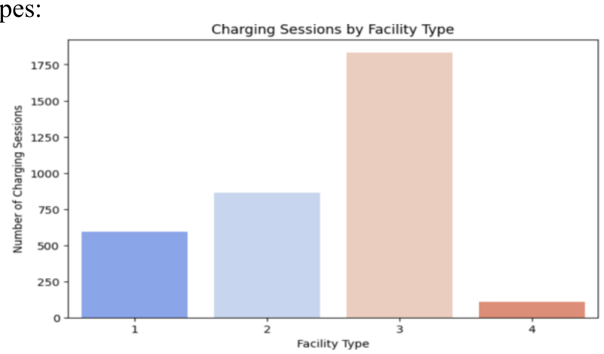


[Fig.6: Total Energy Consumption by Hour of the Day]

iv. *Peak Charging Hour:* The data shows that charging demand reaches its highest point at around 11 AM, when total energy consumption is at its maximum. This means most users prefer to charge their vehicles in the late morning. Figures 5 and 6 clearly show this trend.

C. Charging Facility Analysis

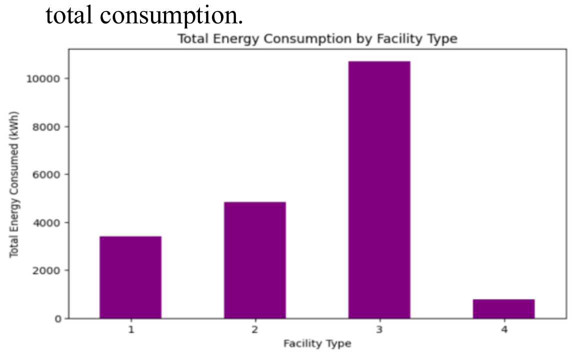
Charging behaviour also varies across different station types:



[Fig.7: Charging Sessions by Facility Type]

i. *Most Utilised Facility Type:* From the graph**,** it is clear that type 3 charging station is the most preferred facility, with 1,832 sessions.

ii. *Facility with the Highest Total Energy Consumption:* From fig.7**,** it is clear that type 3 is the main charging infrastructure, as evidenced by its 10,703.24-kWh total consumption.



[Fig.8: Total Energy Consumption by Facility Type]

iii. *Facility with the Lowest Total Energy Consumption:* From the analysis, it is also evident that the Type 4 charging station has consumed only 779.44 kWh, which indicates that these people have less reliance on this facility type.

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D. Key Insights

The key takeaways from this analysis are:

i. *Weekly Trends:* Charging stations are busier on weekdays, with Thursday seeing the highest number of sessions and Sunday being the quietest.

ii. *Peak Hours:* Most charging happens in the late morning, suggesting that EV owners prefer to plug in their vehicles around mid-day rather than early in the morning or late at night.

iii. *Facility Usage:* Type 3 charging stations turned out to be the most popular. They recorded the most sessions and the highest energy use.

V. CONCLUSION

This study explored how artificial intelligence (AI) is being applied in different areas of engineering, with a special focus on an electric vehicle (EV) charging
dataset from Kaggle. Through exploratory data analysis, we uncovered insights such as which days see the most charging activity, which stations are the busiest, and what times most people prefer to charge their cars.

These observations can help EV charging stations, especially those at workplaces, plan their operations more effectively. For example, workstations could introduce small discounts or rewards for users who charge during less busy hours. This simple step could help reduce rush-hour load and make energy use more balanced. The study shows how beneficial AI and data analysis can be in solving real-world problems. As more people switch to EVs, this pattern will definitely help workplaces utilise their charging facilities more effectively.

DECLARATION STATEMENT

After aggregating input from all authors, I must verify the accuracy of the following information as the article's author.

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- **Data Access Statement and Material Availability:** The adequate resources of this article are publicly accessible.
- **Author's Contributions:** The authorship of this article is contributed equally to all participating individuals.

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