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Electric Vehicle (EV) Charging Technology: Utilising Untapped Potential of Artificial Intelligence (AI) in Electrification of Critical Infrastructure

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Abstract: ***Artificial intelligence (AI) has proven to be an asset in reducing human intervention in predicting and decision-making for many applications. Electrification through the addition of both electric vehicles (EVs) and charging stations is resulting in several core challenges, including improving utilisation, increasing availability, and reducing charging times. This paper aims to develop concepts that AI can be trained on to enable applications such as predicting battery life, making accurate charging-time predictions, and identifying the cheapest available charging options for EV owners. Additionally, a model was proposed to predict with available variables to provide major stakeholders, such as customers with EV purchasing timeframes, businesses with suitable chargers, governments for policy updates, and other stakeholders for carbon footprint reduction measures. Although this concept limits data collection from both manufacturers and customers, relaxing government policies to allow data access may lead to improved AI models. Upgrading charging equipment to enable data collection on customer charger utilisation is a challenge from both manufacturers' and users' perspectives. Users become conscious of their data privacy while sharing information about their vehicles and charging frequencies. Manufacturers become more conscious of their data privacy when sharing typical battery and other equipment characteristics curves, which are more confidential, to ensure they are not readily available to competitors. The holistic conceptual model developed in this paper served as the basis for AI training. The model offers significant opportunities to learn from other published predictive techniques and data analysis methods for critical infrastructure, thereby increasing the safety, quality, and reliability of electrical power.***

Keywords: ***Electric Vehicle Charging Stations, Artificial Intelligence, Electrification, Critical Infrastructure***

Nomenclature:
AC: Alternating Current
AI: Artificial Intelligence
CCS: Combined Charging System
CHAdeMO: Charge de Move
DC: Direct Current
DoD: Depth of Discharge
EV: Electric Vehicle
EVCS: Electric Vehicle Charging Stations
SOC: State of Charge
V-2-G: Vehicle-2-Grid
V-2-G: Vehicle-to-Grid)
V-2-H: Vehicle-to-Home
V-2-L: Vehicle-to-Load
V-2-V: Vehicle-to-Vehicle

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I. INTRODUCTION

Artificial Intelligence (AI) is known to possess key features that enable computers and machines to mimic human abilities. These abilities are not limited to reasoning, learning, decision-making, perception, language understanding and creativity [1]. Humans have trained machines using programming languages that interact with hardware and deliver major products and services across industries, including manufacturing and software development. The core element of AI is machine learning, which enables computers to learn without programming to achieve specific results [2]. For example, a programmed model will generate results by following the encoded algorithm. But an AI model will utilise machine learning techniques, such as regression, correlation, and other statistical tools, to analyse data and predict outcomes. Traditionally, a program runs these analyses, and human intervention is required to determine the exact implications of the results. Some AI experts classify this computer-controlled robot into narrow and general categories. Narrow AI is confined to the type of application that it is designed to deliver—for example, chatbots for customer queries on order shipment details. However, general AI understands broader datasets and performs significantly more human-like in its cognitive abilities. Machine learning and deep learning provide AI developers with tools to train models.

Electrification, with the addition of electric vehicles (EVs) and EV charging infrastructure, is undoubtedly placing a burden on utility companies for power generation and on governments for enforcing policies for multiple stakeholders in the EV industry. Known charging infrastructure technologies with slow and fast charging capabilities at varying power levels require a study to predict key elements of battery life, charging times, and sales planning for both B-2-C and B-2-B markets for EVs and EVCSs. The electric battery is not only the major component of the EV in terms

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of size, but also in terms of cost. Lithium-ion batteries pose several environmental hazards but are relatively safe to operate for EVs. Vehicle safety is a major concern from both the user and the manufacturer's standpoint [3]. Some researchers have predicted and prevented temperature spikes by using AI models. AI has significant potential to predict battery chemistry, enabling optimal use across a given temperature range and improved charging and discharging efficiencies. AI has great potential for predicting designs that save costs [4]. For example, manufacturing processes can be optimised, and production costs significantly reduced. Similarly, predictive models of the overall cost of raw materials and the desired output can promise streamlined manufacturing and significant cost savings.

There are several ways AI models are trained, either using supervision or without supervision [5]. Supervision training involves deep training of the AI by mapping a specified input to an output. However, without supervision, training engages the model to learn from patterns rather than being provided with mapped results. Another method is reinforcement learning, which uses a trial-and-error approach. Neural networks are an excellent tool in machine learning and AI, in which artificial neurons, or perceptrons, are used to analyse data. There are various types of neural networks, including feedforward, recurrent, long-short, convolutional, and generative adversarial [6].

AI engages subsets of the human brain responsible for specific forms of intelligence by solving a given set of problems. Machine learning, neural networks, natural language processing, and game playing are among the major AI subfields. Although artificial neurons were founded in the early 1940s, significant advancements in AI have happened in the past few years. Machine-like human behaviours drive autonomous electric cars and AI assistance. The search engines powered by AI provide results that are analysed and reasoned to a level of understanding that machines were trained for. Some opponents argue that widespread human use has led to a loss of creativity. Still, proponents see this as an opportunity for humans to focus on more intricate tasks that AI may not otherwise perform. The cybersecurity risks to AI pose a challenge, but some researchers have developed AI assistance that is resilient to cyber threats and, at times, operates independently of the internet altogether.

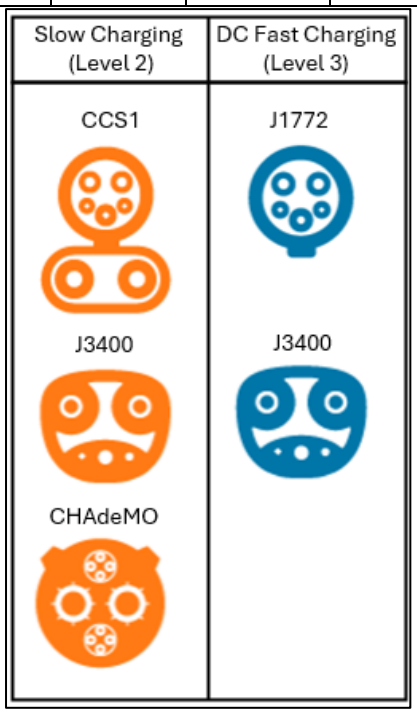
Essentially, EVCSs have varying concepts, such as plug-in, overhead pantograph, and wireless charging [7]. The connectors between the EV and the EVCS not only enable power flow but also establish a communication link for firmware updates and other useful information exchanges, ensuring smooth charging [8] [9]. Level 1 charging uses a J1772 connector for alternating current (AC) charging via a 120V receptacle, allowing the vehicle to be charged at home overnight. Due to longer charging times with this technology, some customers are discouraged from charging when more frequent trips are required. The level 2 charging utilises both J1772 and J3400 connectors to allow comparatively faster charging [10] than level 1 AC charging, but doesn't reduce charging times as much as fast chargers. Direct Current (DC) fast chargers use CCS, CHAdeMO, or J3400 connectors to deliver DC for faster charging. Application-wise, level 1 is more feasible for charging EVs and plug-in hybrids at residential homes, level 2 for both EVs and plug-in hybrids at residential and commercial properties, and DC fast chargers for EVs at commercial properties. Although industry standards accepted and enforced by government agencies ensure safe installation, maintenance, and operation by qualified personnel, the scope of improved designs with efficient charging infrastructure is of great significance for equipment users of both slow and fast chargers. Table 1 shows the types of EVCS in the US.

A. Charging Leads of Connectors

A typical J1772 connector comprises five leads: L1, L2, and PE are 120V line, neutral, and ground; CP (Control Pilot) is for communication and safety; and PP (Proximity Pilot) is for connector detection. CCS and J3400 have similar AC leads as J1772, but CCS adds DC-positive and DC-negative leads, whereas J3400 uses L1 and L2 in DC operation for positive and negative functions. CHAdeMO has two DC power pins, one ground pin, and seven communication and control pins. Figure 1 shows a typical cross-section of a connector.

Table I: Types of Chargers

S. No.	Charger Type	Examples	Applications	Wattage	Time for Full Charge
1	Level 1 (Slow Charger)	Lectron Portable Level 1	EV and PHEV	2.5kW	24 hours
2	Level 2 (Slow Charger)	Enphase HCS 40	EV and PHEV	9 to 12 kW	4-8 hours
3	DC Fast Charger	ChargePoint Express 250	EV only	50 to 350 kW	20 minutes to 1 hour



[Fig.1: Types of Connectors and Pins [11]]

The life span of the EVCS equipment ranges from 10 to 20 years, but the connectors are exposed to mechanical wear and tear from use, and thus will have a reduced lifespan.

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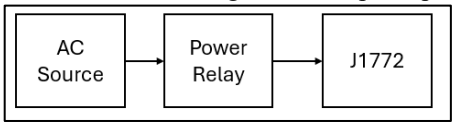
i. AC Slow Charger (Level 2)

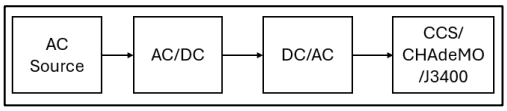
208/240V power from the source is supplied to the EV ports via a power relay for overcurrent protection. Figure 2 shows a schematic of a level 2 charger. The power conduction path is simple, as there is no change in the type of voltage or current waveform. A protective device limits currents within safe limits during a fault condition. Generally, level 2 chargers are available with single- or dual-port options.



[Fig.2: Level 2 Charger]

ii. DC Fast Charger

A DC Fast Charger has a three-phase 480V input power that undergoes an AC-to-DC conversion, followed by a DC-to-DC conversion, before supplying power to the EV ports. Figure 3 shows a schematic of DCFC. There are multiple stages of power conversion, and because of electronic circuitry, there is a risk of harmonic distortion that alters the fundamental voltage waveforms. Generally, DC fast chargers are equipped with a single port with dual connector cords for CCS and CHAdeMO.



[Fig.3: DC Fast Charger]

The major faults that EVCSs experience include network connectivity issues, internal faults or errors, and miscellaneous issues [12]. For example, cellular links are often less reliable in ensuring station connectivity, followed by software freezing, and even less so with connectors and other accessories. This is a key point to note, as the purpose of integrating a communication network for EVCSs is to improve the customer experience both during and after charging. The author in [13] presented the need to lay out an integration of communication systems between the cars being charged and other cars on the commute or parked. Communication errors become a major challenge when the practicality of the concept is in question [13] is concerned.

Bi-directional EV chargers can send power from EVs to the grid; this concept is often called V-2-G (vehicle-to-grid) integration. Some manufacturers, such as Ford Charge Station Pro [14] has capabilities in bi-directional charging. A specialized converter within the EVCS allows sending power back to the grid. Vehicle-to-home (V-2-H) is a similar concept in which a car battery powers the home. Similarly, vehicle-to-load (V-2-L) allows power to appliances and vehicle-to-vehicle (V-2-V) allows power between two vehicles.

According to the US FHWA, more than 192,000 charging ports were installed as of August 2024, with a rate of about 1,000 per week [15]. This underscores the need to ensure a resilient communication network between charging stations and users. Power reliability becomes an issue for utility companies, as EVCS introduces harmonics from the inherent electronic components of AC-to-DC and DC-to-DC power converters. Existing technologies in harmonic reduction using harmonic filters can resolve these issues. The operation of EVCS is safe due to temperature monitoring, automatic shutdown, and high-quality equipment. Their cleaner delivery method reduces the risk of inhaling gasoline fumes while fueling at gas stations. The life-cycle costs of production and end-of-life for an EV provide many advantages in reducing carbon emissions [16]. The benefits of EVs are driving positive change across the world, including at Tata Power in India, which installed more than 60,000 home EV chargers by fiscal year 2024 [17]. Full electrification in India is predicted by 2023 [18]. This indicates a growing EV market in India. Vehicle types vary across different parts of the world. For example, there are more two-wheelers than cars in India. The charging demand for a single charging session for two-wheelers is significantly lower than for cars. Additionally, charging ports differ for two-wheelers from those for cars. For example, the Bajaj Chetak Electric Scooter uses an earthed three-pin household socket with a pin adapter for charging. Given that the scooters have a significantly smaller battery bank, overnight home charging is feasible. However, cars tend to experience longer charging times due to larger battery banks. For the design of a charging infrastructure prospective for the commercial market, the available choices are limited to level 2 and DC fast chargers, given that they offer shorter charging times than home charging via level 1. In these geographies with large-scale two-wheeler markets, the challenges of developing EVCS infrastructure are limited, as home charging becomes a strong candidate for addressing issues arising from the addition of charging infrastructure. Although this is a positive indicator from a cost standpoint, power utilities still face rising energy demand from charging. The author in [19] has proposed using both solar energy and energy management systems to improve energy generation and consumption at residential and commercial properties. The authors in [20] support this and [21], who structure the EVCS system to include both solar energy and grid power.

B. AI for Existing Charging Infrastructure

Researchers are on their way to developing AI models that can predict EV charging behaviour, enabling utilities to be prepared for the rising demand for EV charging. Author in [19] calculated the energy demand from rising electrification based on trends in the industry. However, given ongoing research on training AI models to predict user behaviour, this research offers several advantages for EV transition planning. From the manufacturer's perspective, the use of AI will ensure optimal productivity and the efficient use of raw materials in developing high-performance electric vehicles. For example, an AI model trained to learn the economics of production can predict process improvements much more quickly and reliably using historical data.

Smart charging system that monitors parameters such as voltage, current, charging time, and time, as presented in [22] for policy and technology improvements. Both [22] and [23] proposed inductive charging as a growing area of innovations in EVCS infrastructure. Additionally, aspects of how a lower per capita income impacts EV penetration [23] in developing countries and the scope of AI in developed countries like Malaysia [22] give two sides, challenges and opportunities. Mathematical equations and functions on

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load forecasting and predicting EV charging demand become key for training an AI model to mimic human cognition. An AI trained to develop mathematical equations from its own reasoning is another major application. Electrification, aimed as a solution for sustainable development, drives documentation of challenges with electrification. These challenges, namely limitations on driving range, elongated charging times, and a lack of charging infrastructure [24] [25], pose problems that must be solved using AI.

Engagement of AI in optimal location of EVCS, V-2-G, and battery management and route optimization per [24] With additional considerations for improving battery life through battery diagnostics while plugged into the EVCS, this is a lesser-known aspect in the literature. Dynamic charging management systems, data analytics for charging demand calculations and infrastructure planning are presented in [26] have a limited understanding of the electrical inputs and variables required to ensure its application. This presents an opportunity for current research to document key electrical parameters and market factors that drive changes in EV charging demand prediction, dynamic charging management, and infrastructure planning. [27] bolsters [26] in terms of personalised prices for drivers, when the major issues are related to congestion and queues [27] due to the lack of EVCS with improved charging times. Provisions that allow drivers to select a charger at a dynamic price enable many drivers to either reject or select a charger at a given time. This allows drivers to take advantage of dynamic prices, and thus, demand evens out from the users' side. This concept is similar to the time-of-day tariff, but an AI model trained to determine when to raise prices to smooth utility companies' demand curves is a prospect for AI. Whereas the training and maintenance of the EVCS are key to improving its performance for users, AI-enabled training for technicians boosts the charging station's performance [28]. When AI can access a wide range of training programs and specialised learning tools, some training for the maintenance and operation of EVCSs may become easier to understand and better suited to technicians based on their educational backgrounds.

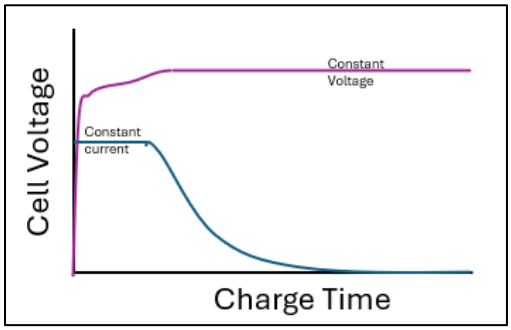
Modern AI strategies, such as Gaussian combination models, address average issues in wrong readings and streamline profiling, augmentation, forecasting, explainability, and charging efficiency through AI-driven solutions [29]. Dynamic pricing based on uncontrolled, controlled, smart, and indirectly controlled [30] poses several challenges for each type, but smart techniques can balance supply and demand. This modelling incorporates both scheduling and forecasting in real time to enable closed-loop communication among the utility, EVCS, EVs, and other system variables. Studies projected inexpensive ways to implement AI for EVCS [31] reviews open the doors when cost is a driving factor for the change. Additionally, predictions for investments using fuzzy decision-making modelling [32] widen the door for financing opportunities for EVCS. A driver safety improvement feature using AI has precedence over other AI applications when reliable forecasts of energy usage and carbon emission reductions are concerned [33], But autonomous features in cars [34] are predominantly derived from AI models that can replicate human-like abilities in reasoning and implementing solutions faster and more efficiently, without compromising driver safety.

II. METHODS AND CONCEPTS

This section prepares some concepts for training AI models. The methodology is to review the literature and industry practices to document recent developments in AI applications for EVCS to track battery health, usage patterns, and consumption, among other metrics. Based on available research, the areas where AI applications add value were identified. The concepts were presented to provide key parameters for collecting data from existing vehicles while charged at EVCS, and to train the AI model using past data to generate results. General AI becomes a more powerful tool here, as it provides a wider range of support than being limited to a specific aspect of electrification. However, this model begins with supervised training but switches to unsupervised training after extensive trial-and-error to achieve accurate predictions.

A. AI for Battery Diagnostics

Battery diagnostics help batteries last longer by identifying cell degradation and other voltage and temperature abnormalities. Tools are available to record the state of charge, health, and cell performance. Figures 4, 5, and 6 show a typical charge-discharge curve for a Li-ion battery. When a typical charge curve from a given manufacturer is compared with actual charge and discharge curves, typical results can be drawn on battery diagnostics. Generally, batteries are rated by a given C rating, so the discharge curve corresponds to that C rate. However, the EV's operating temperature varies. The curve will vary depending on the EV's operating temperature. Depending on the depth of discharge (DOD) percentage, the cycle life increases or decreases. For example, a cell at 1000 cycles at 80% DOD will have 1200 cycles at 65% DOD. An AI model trained to draw comparative results and provide recommendations on battery repairs or preventative measures is an excellent application of AI. Typically, EV batteries are designed to allow 1500 to 2000 charge/ discharge cycles from 0-100% SOC (state of charge) and 100%-0% DOD (depth of discharge). Authors in [35] presented deep learning to predict SOC based on the temperature and C rate variations. So, such methodologies serve as input data for the AI model's comparisons (see figure 7), in addition to manufacturers' available data.



[Fig.4: Charge and Discharge Curve EV Battery [36]]

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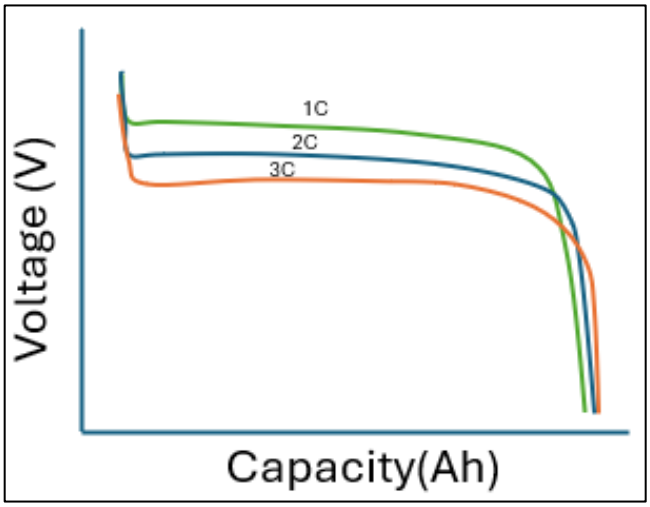
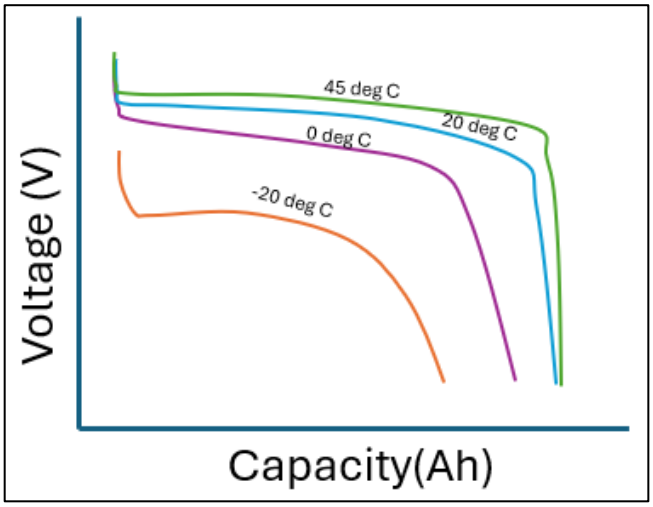
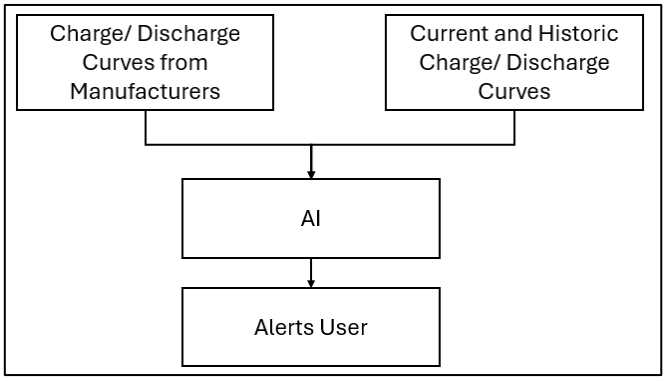


[Fig.5. Discharge at Varying C-rate [36]]



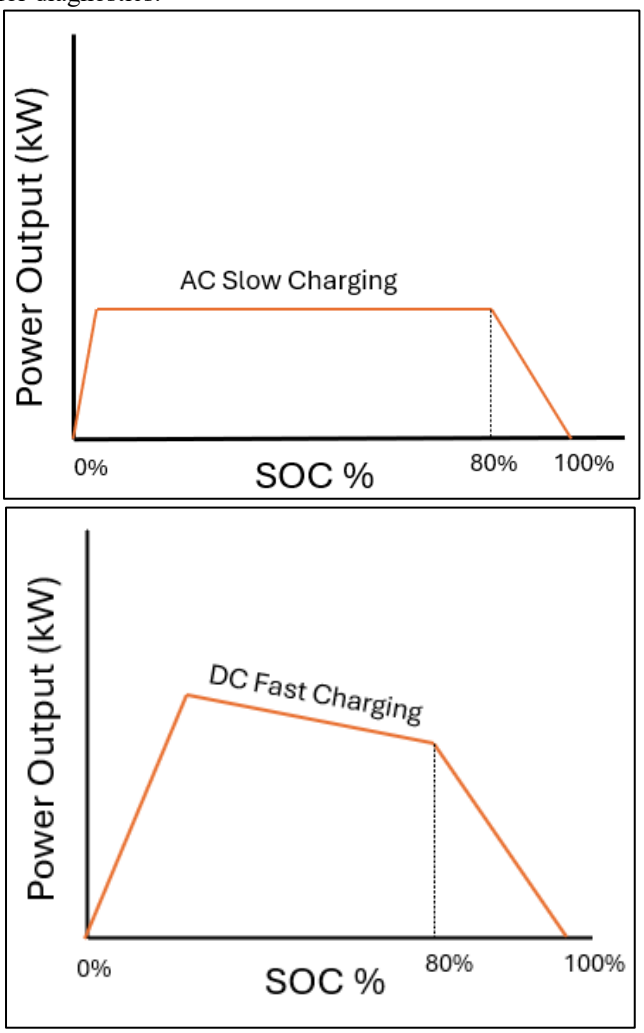
[Fig.6: Discharge at Varying Temperatures [36]]



[Fig.7: AI for Battery Diagnostics]

B. AI for Tracking Charging Sessions

Electric vehicle charging sessions for individual vehicles, recorded by make/model, age, and state of charge when connected to the EVCSs, can be used by AI models trained to predict optimal charging times for the vehicle's new or aged battery. The system will rely on charging session curves per manufacturer, real-time documentation during the session, and data available from vehicle history. Upon comparison, the AI models can not only predict charging times efficiently but also use this information to convey any waiting times of the following customers. Additionally, when integrated with utility bill information, these AI models can predict the optimal price per kWh for customers and the optimal SOC level to ensure batteries remain healthy and last longer. Typically, both EV and EVCS manufacturers publish charging curves as shown in Figure 8. However, as batteries age, the curve may shift. Still, a trained AI model with vast data from all cars on the road will ensure the best data points for analysing customer behaviour while they are plugged in during charging sessions. This ensures customers have readily available information by avoiding visits to mechanics for diagnostics.



[Fig.8: Charging Curves [37]]

C. AI for Predicting Energy Demand

Although the US FHWA records data on several electric vehicle types, ranging from light to medium and high duty, an EVCS serves as a data collection point for the number of electric vehicles, their visit frequency, and energy consumption. This allows a trained AI model to predict typical demand for electric vehicles at a given time of day and prepare utilities to ensure sufficient power generation. This allows utilities to promptly gauge the need for new power generation stations, reducing any impacts from electrification. When customers' charging patterns are analysed using an AI model, the predicted usage of charging stations is highly accurate. Some additional inputs to the model include government policies, supply chain issues, customer social media reviews, and so on. This is

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based on the fact that stock prices vary depending on many political factors and market conditions. For example, Tesla Motors saw a rise right after the 2024 election results in the United States. Some models presented in [19] encouraged factoring in energy consumption per mile and improving battery efficiency over time when predicting energy demand from the EV transition. An AI model, when trained to provide useful data for demand calculations and given keywords, becomes a great tool. The challenges in collecting vehicle information and charging frequencies may raise privacy concerns, but policies to protect the safe use of data and ensure resilience against cyber threats are a topic of research and a major ethical concern.

D. AI for Predicting Ideal Car Purchases and EVCS Purchases

The rate of EV transition depends on several factors, including government policies, global supply chains, market conditions, utility companies, customer behaviour, customer income levels, business capital budgeting processes, and so on. A user with predictive models that suggest ideal EV purchases based on all applicable factors at a given time drives a successful EV transition. When applied to policymakers, this tool can help develop policy improvement plans to accelerate the transition. When applied to customers, they can plan the purchase of EVs and home charging equipment. For commercial applications, many businesses may benefit from knowing how many chargers they require for a given year, along with the total number of EVs they purchase each year.

E. AI for Predicting EVCS life

The charging-current data from EVCS-to-EV charging sessions serve as a data source for predicting the useful life of the EVCS equipment. For example, variations in temperature and load current through electrical conductors and connectors affect insulation resistance and the lifespan of the conductors. Based on manufacturers' data on conductor insulation resistance and measured values during charging sessions, many conclusions can be drawn about the useful life of cables and connectors. This information, communicated via the network, when shared with equipment owners, enables prompt or planned replacements based on AI predictions and recommendations. Additionally, the AC-to-DC and DC-to-AC converter efficiency and operating curves from manufacturers serve as a point of comparison with the measured curves. These, again, are predicted by an AI-trained model for the useful life and faults within the given sub-components of the EVCS.

F. Advantage of AI Integration

All customers, manufacturers, utility companies, governments, and other stakeholders are informed about the best AI predictive results derived from available real-world data from EVCSs. This allows the government to improve its policies, manufacturers to improve the design of both EVs and EVCS, utility companies to increase power generation, and customers to enhance their experience through improved electric vehicle health monitoring and usage. Allows an increase in technical support services for the products with AI integration, thereby increasing demand for skilled labour. It provides firms with opportunities to leverage global expertise by outsourcing key engineering support services, thereby offsetting the increased costs associated with AI integration. It may draw the attention of major businesses worldwide to collaborate. Many open-source platforms offer AI at no cost, making them promising for developing nations, where additional costs for networked chargers and AI integration are challenging.

G. Challenges with AI Integration

Many EVCS at existing locations are non-networked, and converting them to the networked option is a hurdle, especially given chargers' 10- to 20-year useful life. In contrast, many chargers installed in the past are still within their own. Additionally, the availability of chargers capable of recording information, as studied in Section 2, requires major upgrades to the existing equipment. There will be cost implications for these modifications, and some manufacturers may continue to produce them as they are used unless policymaker's mandate otherwise. So, this becomes a topic of discussion with policymakers to ensure standards mandate networked chargers capable of recording user information of varying types during each charging session.

H. AI for Customers with Accurate Results

An additional feature of the existing user interface inside the cars becomes crucial for alerting customers to issues with their electric vehicle, such as a poor battery condition. Providing optimal, suggested charging intervals and times to customers via the same user interface not only improves the customer experience but also allows manufacturers to gain market share for their vehicles with integrated AI technologies. The chatbots have significantly reduced customer care costs for major e-commerce platforms, so similar cost savings from AI integration in EVCS translate into lower EV repair and diagnostic costs per visit. Each charge session serves as a checkpoint for customers' vehicle health.

III. OVERALL AI CONCEPT MODEL (PRACTICAL APPLICATION)

A holistic picture of the alerting and notification system is shown in Figure 9. There is significant potential in AI when all electrical characteristic curves for both EV and EVCS, industry standards, and electrical measurements from EVCS and EV are utilised as a training dataset. Thus, AI eventually starts alerting, notifying, and assisting with decision-making processes for all: customers, manufacturers, utility companies, government, and other stakeholders. Here, the significance of engagement of industry experts familiar with both battery and charging infrastructure design is necessary when supervised training is provided to AI initially, until it becomes capable of getting trained without supervision.

The input block for AI is primarily governed by data availability from multiple sources, including manufacturers' published data, ongoing research, and industry standards. The actual measured readings for several electrical parameters, such as voltage, current, battery SOC, and so on, form

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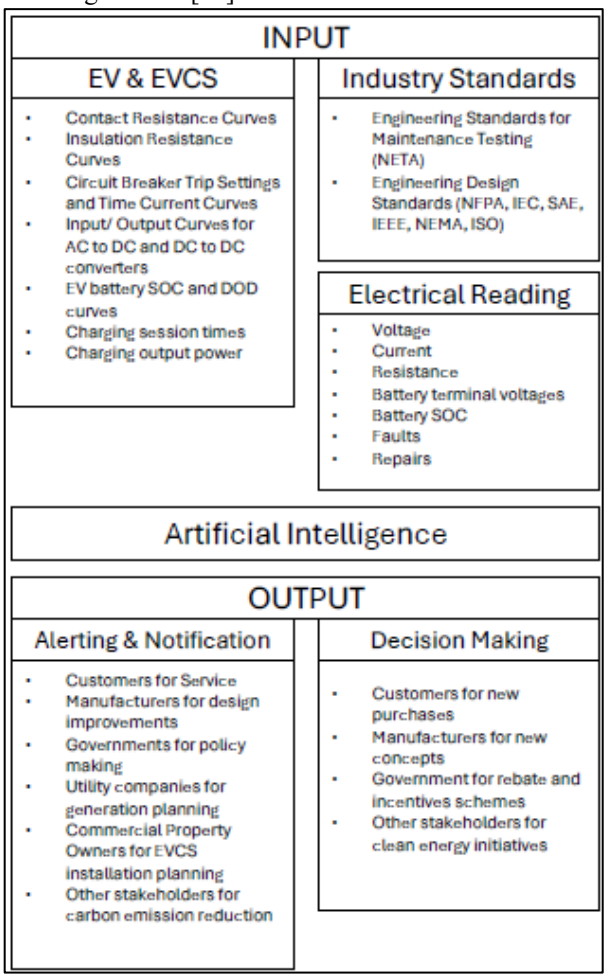
a dataset for an AI model to support further analysis of other vehicles, along with known resources. Additionally, once some of the inputs on market conditions, government policies, supply chain issues, and so on are integrated into the system, AI becomes capable of making more informed decisions for all stakeholders. Such modelling can be optimised using available research methodologies in [38] and forecasting tools in [39].



[Fig.9: Holistic AI Model]

IV. CONCLUSION AND DISCUSSION

The methodology relied on a literature review to understand AI and the available technologies in EVCS infrastructure. The development of AI for EVCSs is seen as a promising area with significant potential to improve the customer experience with EVs. The electrical characteristics of batteries and EVCS subcomponents, when provided to manufacturers as SOC and DOD curves at varying temperatures, serve as data points for the AI to be trained on. Additionally, vast amounts of customer data collected during charging are added to the system, continuously training the model on real-world data. An AI model capable of analyzing the data with many statistical tools and drawing conclusions for customers, utilities, and government on battery life, next service, EV purchasing suggestions, EVCS addition plans, policy changes, and energy demand predictions is certainly an asset when AI has a promising future in reducing human efforts, wherein it can mimic human-like cognitive powers. After a comprehensive literature review, a holistic AI training model was developed, with potential benefits for major stakeholders across the entire EV and EVCS domain. The major limitations start with limited knowledge of AI applications for EVCS in predicting energy demand curves, improving charger utilisation, and supporting policy-making. However, these limitations served as the basis for conceptualising the holistic model.

The challenges of collecting user data threaten data privacy. More resilient software systems against cyber threats are a solution to this issue. Many data points that AI learns from the real world are useful to manufacturers in innovating their products for customers. For the government, a readily available tool will help with major policy changes to increase widespread adoption. Charging time with available equipment is known to manufacturers from tests and trials with limited operations. However, when such AI-generated predictions from more real-world data points become readily available, EVCS design optimisation can offer improved charging times and efficiencies. Thus, the model offers significant opportunities to leverage other published predictive techniques and data analysis for critical infrastructure, thereby increasing the safety, quality, and reliability of electrical power.

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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- **Funding Support:** This article has not been funded by any organisations or agencies. This independence ensures that the research is conducted objectively and free from external influence.
- **Ethical Approval and Consent to Participate:** The content of this article does not necessitate ethical approval or consent to participate with supporting documentation.
- **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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