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Intelligent Integration: Harnessing Artificial Intelligence for Enhanced Performance and Efficiency in Electric Vehicles

Journal of Electrical Systems

Abstract:- *The transition towards electric vehicles (EVs) necessitates the development of efficient and reliable charging infrastructure. This paper presents an AI-driven approach to optimize EV infrastructure, focusing on five key aspects: profiling, augmentation, forecasting, explainability, and charging efficiency. Profiling involves understanding EV drivers' behaviors and preferences, facilitating targeted infrastructure development. Augmentation utilizes AI algorithms to identify optimal locations for new charging stations or upgrades based on usage patterns and demand forecasts. Forecasting models leverage machine learning techniques to predict future EV adoption rates and charging demands, aiding in infrastructure planning. These datasets can be used to generate insights and decisions through the use of artificial intelligence (AI) algorithms. A thorough analysis of the usefulness of AI in charge-demand profiling, data augmentation, demand forecasting, demand explainability, and charge optimization of the EVI has not yet been conducted, despite a number of recent studies in this area. This study's goal was to create, develop, and assess a thorough AI framework that fills in this EVI gap. The findings of an empirical assessment of this AI framework on an actual EVI case study validate its usefulness in tackling the new issues surrounding dispersed energy resources in the deployment of EVs.*

Keywords: *Ai-Driven, Electric Vehicle, Infrastructure, Profiling, Augmentation, Forecasting, Explainability,*

1. INTRODUCTION

Electric vehicles (EVs) are becoming more and more popular as a vital weapon in the fight against climate change and the reduction of greenhouse gas emissions worldwide due to the spike in demand for environmentally friendly transportation options [1]. A strong and effective charging infrastructure is required to facilitate the widespread adoption of electric vehicles (EVs), as customers and governments alike choose greener alternatives to conventional gasoline-powered vehicles [2]. However, the quickly changing needs of this expanding industry may prove too much for the conventional approaches to designing and implementing infrastructure to keep up with. Using artificial intelligence (AI) technology offers a strong way to overcome this difficulty and has the ability to enhance EV infrastructure in a number of ways. AI technology makes it possible to optimize EV infrastructure in a variety of ways beyond what can be achieved with traditional techniques [3]. Through the utilization of AI techniques, namely machine learning and data analytics, planners can acquire significant understanding of the intricate and ever-changing patterns of electric vehicle consumption and demand. With the help of these data, infrastructure planners can make better decisions and install charging stations more strategically by taking into account variables like user behavior, traffic patterns, and population density [4].

Additionally, planners can anticipate future needs and proactively allocate resources accordingly by using AI-driven forecasting models, which can provide accurate estimates of future EV adoption rates and charging demands [5]. This predictive capability allows infrastructure to be planned and implemented with future growth in mind, which is crucial for guaranteeing the scalability and sustainability of EV infrastructure over time.

A. Profiling

Understanding the varied needs and behaviors of EV drivers is one of the core components of optimizing EV infrastructure. Profiling is the process of examining past data to find trends in the usage choices, travel itineraries, and charging habits of various user groups [6]. The creation of thorough profiles of EV drivers by EV infrastructure planners using AI techniques, such as machine learning and data analytics, enables targeted infrastructure construction that corresponds with the unique requirements of various localities and user groups [7].

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B. Augmentation

The expansion of the electric vehicle (EV) market necessitates the upgrading of the charging infrastructure in order to meet the increasing demand and guarantee broad accessibility. When it comes to choosing the best places for new or upgraded charging stations, AI-driven algorithms are essential [8]. These algorithms take into account variables like population density, traffic patterns, and the accessibility of current infrastructure [9]. AI may help decision-makers strategically deploy charging infrastructure to improve coverage and convenience for electric vehicle users while minimizing costs and environmental effect. It does this by analyzing real-time data and prediction models.

C. Forecasting

Precise projections of EV adoption rates and charging requirements are necessary for efficient infrastructure planning. Advanced statistical methods and machine learning algorithms are used by AI-powered forecasting models to evaluate past data and project future trends in EV demand and consumption. These models give infrastructure planners the ability to foresee future requirements and proactively allocate resources to meet increasing demand, guaranteeing the scalability and sustainability of EV infrastructure over time. These factors include economic indicators, policy changes, and technological advancements.

D. Explainability

When implementing AI-driven solutions for electric vehicle infrastructure optimization, transparency and trust are crucial factors to take into account [10]. The goal of explainability techniques is to increase stakeholder awareness and accountability by offering insights into the AI algorithms' decision-making process. Infrastructure planners may resolve bias and fairness issues, explain the reasoning behind infrastructure decisions, and promote increased cooperation and engagement within the EV ecosystem by utilizing interpretable AI models and visualization tools.

E. Charging Efficiency

To improve user experience and grid dependability, boosting charging efficiency is essential in addition to expanding and optimizing infrastructure coverage. AI-driven optimization strategies can reduce costs and environmental impact while assuring the dependable and sustainable functioning of EV charging networks. These techniques can help decrease charging times, optimize energy distribution, and alleviate peak demand surges. Artificial Intelligence (AI) facilitates dynamic management of charging infrastructure to adjust to changing conditions and customer preferences by combining real-time data analytics, predictive modeling, and smart grid technologies. This eventually improves the efficacy and efficiency of EV charging networks.

2. REVIEW OF LITERATURE

Alqahtani and Kumar (2024) examine the complex field of transportation security, with a focus on how machine learning might be used to strengthen safety protocols in systems for electric and flying vehicles. This study's thorough analysis emphasizes how important it is to use cutting-edge technologies to reduce the security threats associated with new forms of mobility [11]. Researchers, legislators, and industry stakeholders working to improve transportation security in the face of changing technological landscapes can benefit greatly from the authors' perspectives, which are synthesized existing literature and offer insights into the application of machine learning algorithms.

Bandaragoda et al. (2020) provide a novel framework that profiles commuter behavior using artificial intelligence and the Internet of Things (IoT), enabling real-time transportation management decision-making [12]. The suggested approach provides actionable insights into commuter behavior patterns through the wise integration of IoT sensors and AI algorithms, empowering stakeholders to improve operational efficiency and optimize transportation systems. This study emphasizes how AI-driven methods have the ability to completely change commuter-focused transportation services, resulting in the development of safer and more sustainable urban mobility ecosystems.

Fotouhi et al. (2019) adds to the body of literature by putting forth a broad model to comprehend the charging habits of electric vehicle (EV) drivers, a crucial component of infrastructure for sustainable transportation. Through the use of sophisticated modeling tools and actual data, the authors clarify the complex dynamics influencing EV charging trends [13]. This model establishes the groundwork for developing a reliable charging infrastructure and putting into practice efficient demand-side management techniques in addition to offering insightful information to legislators and energy planners. The study emphasizes how crucial predictive modeling is to improving EV charging infrastructure and accelerating the shift to more environmentally friendly transportation systems.

Gunning et al. (2019) provides a thorough introduction to Explainable Artificial Intelligence (XAI), highlighting the significance of interpretability and transparency in AI systems. The writers open the door for increased accountability and reliability in AI-driven decision-making processes by clarifying important ideas, approaches, and difficulties related to XAI [14]. This groundbreaking work provides insightful analysis for scholars, practitioners, and politicians debating the moral and societal ramifications of artificial intelligence (AI) through a synthesis of many methodologies, from rule-based systems to model-agnostic tools. XAI has the ability to democratize access to AI-driven insights while reducing the dangers of algorithmic bias and unexpected consequences by promoting a greater understanding of the underlying workings of AI systems.

Kempitiya et al. (2020) add to the body of knowledge by putting forth a novel artificial intelligence framework for bidding strategy optimization in multiple frequency reserve markets, where uncertainty presents serious difficulties. Through the utilization of sophisticated machine learning algorithms and optimization methodologies, the writers create a sturdy framework that can adapt bidding strategies to fluctuating market conditions [15]. The study illustrates the effectiveness of the suggested framework in raising bidding efficiency and optimizing income generation for market players through empirical validation and case studies. This research highlights the revolutionary potential of AI-driven approaches in solving complex decision-making problems in dynamic and uncertain situations, while also advancing the state-of-the-art in energy market optimization.

3. PROPOSED AI FRAMEWORK

The lowermost layer of Figure 1 shows how the proposed AI structure capabilities inside the digitalized EVI. The transmission organization and dissemination and utility control places, as well as other upper levels of a normal shrewd lattice, give information and interchanges to the EVI, as explained. It would likewise get immediate feeds from neighboring microgrids that utilization environmentally friendly power sources. Figure 2 shows the parts of the proposed AI framework, which comprises of five modules supported by a focal EVI information lake. The five modules' keen cycles, significant results, and information inputs are diligently kept in this information lake, which makes it simpler to address information for both present and future EVI exercises. Inside the savvy lattice, this layer of information portrayal can be utilized for both progressive and parallel correspondence. The recommended AI engineering comprises of five modules: gauge explainability, EV charge-request forecasting, EV information augmentation, charge-request profiling, and EV charge advancement. Figure 2 additionally shows how information and experiences stream between these five modules and how the system is created consistently, with charge enhancement taking care of back more than once into request profile for the ensuing EVI use cycle. This system's parts manage an assortment of AI capabilities, including affiliation, profiling, forecast, and streamlining. The k-implies calculation, multivariate relapse, deterministic improvement, and Gaussian combination models (GMM) can be utilized to sum up the calculations used for these abilities.

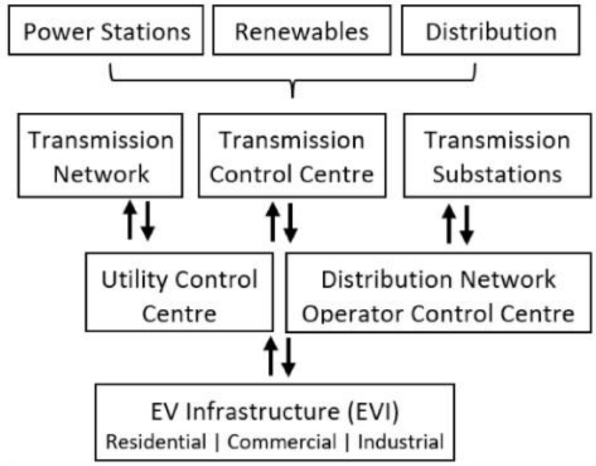

Figure 1: EVI's hierarchical composition in a smart grid environment.

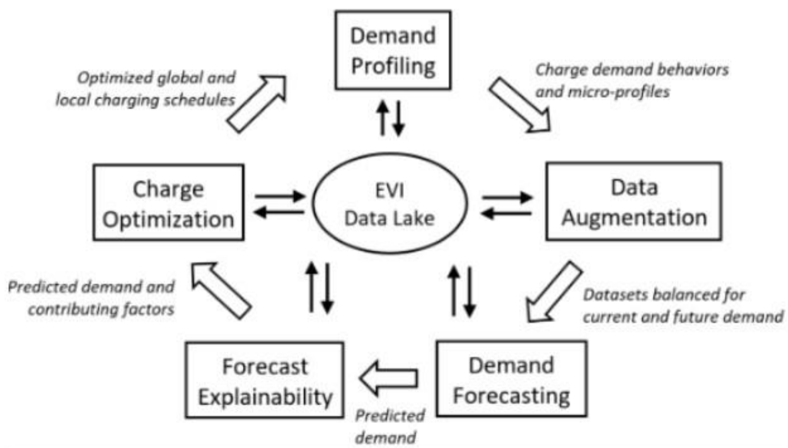

Figure 2: AI framework for electric vehicle infrastructure (EVI) that is being proposed.

4. COMPONENTS OF THE AI FRAMEWORK UNDER CONSIDERATION

Here, we inspect the AI usefulness and algorithmic capacities of every one of the five modules. In each subchapter, an observational evaluation of each and every module is additionally given, and this present reality contextual investigation of the Versatile Charging Organization (ACN) from Caltech is utilized. Two versatile charging networks on the Caltech grounds and one at the Fly Drive Lab (JPL) office gave ACN information to assortment. This dataset offers far reaching data about each charging meeting and mirrors a hybrid of a public and working environment charging station.

4.1 Data Augmentation

Lopsided information, a limited quantity of complete information, and wrong or missing numbers are normal issues with EVs and EVI information streams. This is an unexpected issue that man-made reasoning devices can settle. Notwithstanding the first information sources, the interest profiles feed into this module to approve and illuminate the augmentation cycle, as referenced in the proposed AI system. The ACN dataset which addresses a work environment accusing circumstance of roughly 30,000 charging meetings from 52 electric vehicle supply gear (EVSE) or quick charging ports, is where we showed information augmentation. The Gaussian blend model (GMM) approach, a solo learning strategy, was utilized to enhance information. A weighted amount of Gaussian part densities is utilized to address the data of interest in a GMM, which depends with the understanding that the information focuses are gotten from a combination of a limited number of Gaussian dispersions with obscure boundaries. They are an augmentation of k-implies bunching that considers the covariance construction of the information as well as dormant Gaussian capabilities. Expecting that expanded information are created utilizing an accusing station of q quick charging focuses is the first move toward quite a while augmentation process.

$$P(X|\theta) = \sum_{K=1}^{K} \pi_K \frac{exp\left(-\frac{1}{2}(||X-\mu_k||)^2 \Sigma_k^{-1}\right)}{\sqrt{(2\pi)^3\, det(\Sigma_k)}} \qquad [1]$$

To make new data of interest, the Gaussian capabilities that came about because of the estimation with K=10 were utilized. Eight, one, and one Gaussian capability were utilized to fit the green, orange, and red bunches, individually. At first, 7500 new examples — generally 25% of the underlying complete dataset — were created from each of the three profiles. Utilizing the timestamps as an aide, wrong information was killed from the subsequent examples. For example, the date that was obtained must be a genuine date, the association time should not be not exactly the disengaged time, and the charging completed time couldn't be more limited than the detached time. The quantity of new examples was brought down to 3395 by this separating. Incongruous examples were dispensed with on the grounds that, as indicated by the first reason that the charging office had 52 quick charging focuses, something like 52 EVs could be charged on the double. The ensuing AI module for charge request forecasting utilized this upgraded dataset.

4.2 Demand Forecasting

This module figures the energy interest for EVI for the next day, and the model explainability yield for the accuse advancement is consolidated of these gauges in the last module. Table 1 sums up the measurable parts of the daily energy conveyance dissemination. Days when there was no energy conveyance were prohibited, in view of the presumption that the infrastructure for charging had an issue. Throughout the whole dataset, a normal of 33.05 charging meetings and 31.6 clients each day were noticed.

Table 1: The daily energy-delivered distribution's statistical properties.

Statistical Parameter	Value (kWh)
Mean	512.9
Standard deviation	563.7
Minimum value	3.15
Quartile 1	81.2
Quartile 2	582.2
Quartile 3	823.2
Maximum value	1425.71

With a mean utilization of 512.9 kWh and a sizable standard deviation of 563.7 kWh, the measurable examination gives useful details about the energy utilization dataset and demonstrates huge changeability in energy use over the noticed period. The least recorded energy utilization of 3.15 kWh demonstrates times of rarely low use, and the most noteworthy recorded utilization of 1425.71 kWh shows times of huge energy interest. The quartile values give further knowledge into the appropriation of energy use. For instance, the main quartile (Q1), at 81.2 kWh, shows that 25% of the information are beneath this level. The third quartile (Q3), then again, is 823.2 kWh, which demonstrates that 75% of the dataset is beneath this sum. Inside the dataset, the subsequent quartile (Q2), or 582.2 kWh, addresses the middle utilization, which fills in as an essential issue of reference. The reach, dispersion, and focal propensity of energy use are all around addressed by these factual boundaries, which lay the preparation for extra examination and judgment in projects including energy the executives and arranging.

Table 2: The daily energy-delivered distribution's statistical properties.

Regression Algorithm	Model	RMSE	MAE	COD
XGBoost	Model A	114.412	71.312	98.412
	Model B	121.082	70.141	99.525
	Morning model	14.041	8.125	70.162
	Evening model	121.082	70.352	98.325
AdaBoost	Model A	171.625	151.714	80.414
	Model B	160.060	125.325	87.325
	Morning model	16.825	14.225	50.414
	Evening model	144.090	132.252	89.412
Linear regressor	Model A	182.825	152.525	83.717
	Model B	181.855	152.414	85.771
	Morning model	13.082	8.410	70.262
	Evening model	182.324	151.714	86.625
Multilayer perceptron	Model A	114.925	80.141	95.714
	Model B	101.825	70.082	98.825
	Morning model	12.925	8.141	70.141
	Evening model	95.714	71.312	96.714
Random forest	Model A	99.252	60.625	96.714
	Model B	103.088	60.714	95.252
	Morning model	14.825	7.251	70.162
	Evening model	121.714	60.141	82.041
Support vector regression	Model A	125.714	125.825	88.256
	Model B	101.625	162.252	71.258
	Morning model	15.061	8.236	70.412
	Evening model	152.414	151.625	79.152

The investigation of relapse calculations offers significant experiences into how well various models gauge energy use. Root mean square mistake (RMSE), mean outright blunder (MAE), and coefficient of assurance (COD) measurements are utilized to assess prescient precision across different calculations and their relating models; lower values signify more noteworthy execution. The Multi-facet Perceptron (MLP) and XGBoost models routinely show serious execution; the RMSE of Model B of MLP is 101.825, while the RMSE of Model B of XGBoost is 121.082. These models have relatively low expectation mistakes for energy use, showing that they are effective in distinguishing fundamental patterns in the information. In contrast with XGBoost and MLP, AdaBoost and Backing Vector Relapse

(SVR) models show lower mistakes in spite of their moderate presentation. Curiously, all calculations show that morning models have less blunders than night models, recommending that examples of energy use might adjust over the course of the day. In light of everything, the evaluation demonstrates the way that well a few relapse calculations and models can gauge energy use, offering clever data for energy the executives and navigation.

4.3 Optimizing Maximum EV Demand

Around here, our main objective is to augment the interest for electric vehicles after some time through charge improvement. Its bits of feedbacks incorporate the accompanying: the most extreme interest that can be obliged at some random time during the given time frame, the anticipated interest (utilization) for the given time span (addressed by the set T), the favored time span (addressed by $Tpref$), and the ruling steady (α). Here is the introduction of the deterministic advancement issue's numerical plan.

Optimize:

$$\sum_{i\in T} d_t^{EV} \quad [2]$$

$$\sum_{i\in T}\left(d_t^{EV} + d_i^{butld}\right) \leq D_{tot} \quad [3]$$

$$\forall t \in T, \left(d_t^{EV} + d_i^{butld}\right) \leq D_{max} \quad [4]$$

$$\frac{\sum_{I\in}(T-T_{Pref})d_t^{EV}}{\left(T_{Size}-T-\frac{T}{pref}\right)} \leq \alpha size\, \frac{\sum_{i\in} T_{pref}\, d_i^{EV}}{T_{ref}^{p}} \quad [5]$$

Amplifying the general interest for EVs inside the predefined time span was the definition's objective. While constraint limited the greatest reasonable interest, constraint dealt with the interest balance. To keep the solver from becoming stalled in the undeniable answer for this sort of issue — having a pinnacle EV interest on negligible structure request time steps — constraint was set up as such It dealt with the interest for EVs by spreading it more toward the ideal time period (see Figure 1). Moreover, we included α ($0<\alpha\leq1$) to deal with the predisposition for the ideal time period. It moved more for the ideal time span as it moved toward 0 as well as the other way around.

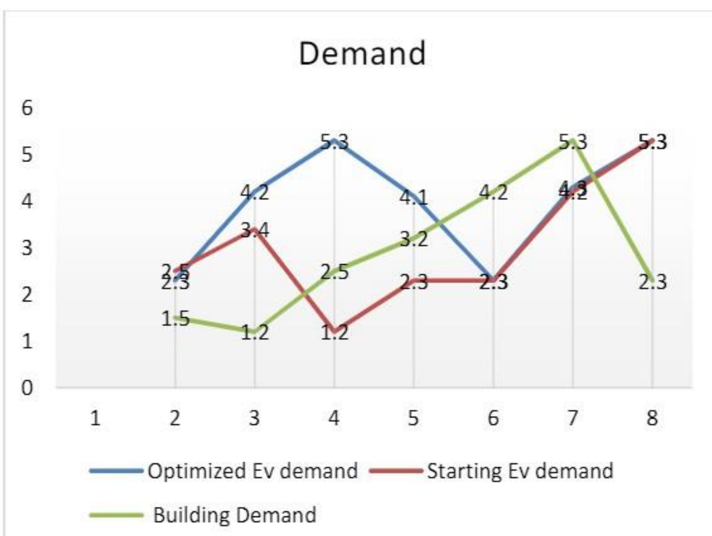

Figure 1: EV demand optimization.

Experiment 1—Optimizing maximum EV Demand

We evaluated the module for amplifying the interest for electric vehicles in this analysis. It required the accompanying data sources: the complete interest and greatest interest that the structure can oblige (which were well defined for the structure and had a steady worth); the favored time span (which was picked by the EVI and set to 5 am to 8 am and 5 pm to 8 pm); and the anticipated EVI/building interest (considered gave from the EVI). It was chosen to set the overwhelming steady (α) to 0.2.

Furthermore, we evaluated the indistinguishable analysis both with and without the constraint (to understand the effect of. Though Figure 1 shows the results of the restricted advancement, Figure 1 shows the results of the unconstrained streamlining. It is obvious that the constraint module endeavored to push a sizable part of the interest for EVs toward the ideal time period.

Experiment 2— Optimizing Target EV Demand

We surveyed the module for amplifying the expected EV interest in this preliminary. It utilized the EV request expectation module's assessed interest for EVs for the predetermined time span. The constants and constraints were equivalent to in the earlier analysis.

The examination's outcomes are shown in Figure 2. (Here, the outcomes are not restricted). The assessed interest for EVs was esteemed at 1700 kWh.

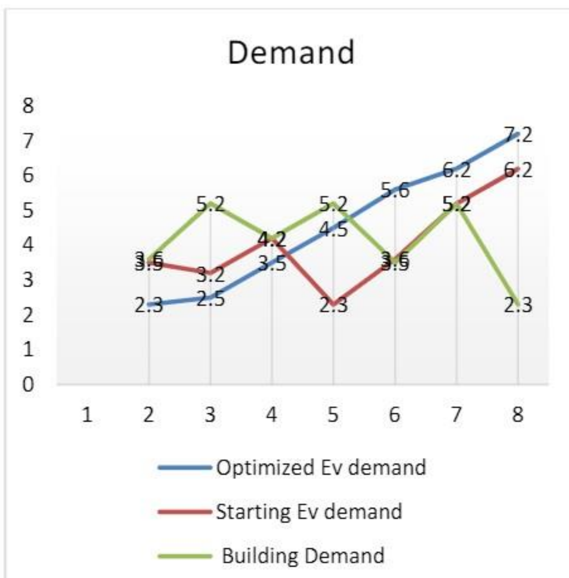

Figure 2: Target EV demand optimization.

Experiment 3—Optimizing EV Charge Scheduling

We surveyed the EV planning advancement module in this trial. It required the charging needs (in kWh) and the ideal charging time for every EV. The example information for the initial five EV clients is displayed in Table 3.

EV-ID	Charge Amount	Start Time	End Time
1	40	13:00	08:00
2	51	13:00	08:00
3	46	12:00	07:00
4	20	08:00	11:00
5	41	04:00	11:00

The given EV charging information shows one of a kind charging ways of behaving, with contrasts in charging times and meeting start times among different electric vehicles. Certain EVs require charging for expanded timeframes — short-term or into the night — while others decide for more limited noontime charging meetings. These discoveries exhibit the assortment of EV proprietors' preferences and utilization propensities. Settling on very much educated conclusions about matrix the executives and charging infrastructure advancement is made conceivable by the investigation of such information. Partners in the shift to electric versatility can further develop client experience generally speaking, empower sustainable energy ways of behaving, and fabricate more proficient charging arrangements by observing EV charging patterns.

4.4 Results Analysis

From this system, we can remove the accompanying examination and results for every one of the five modules. Various significant profiles along the significant investment use aspects were distinguished by the interest profiling module. Significant information from interest profiling was likewise utilized in the interest forecasting stage. Model execution was improved, as indicated by the outcomes, by reproducing client conduct on every one of the groups found during the profiling system. Utilizing XAI and SHAP, the top-performing request conjecture model was utilized to decide the contributing highlights. This showed the basic significance of the three-day moving normal and the day of the week. It follows that most of EV charging propensities relied upon the day of the week and how much charging that had happened in the past couple of days. Contrasted with the earlier week, the seven-day moving normal showed a diminished component importance, proposing that clients were not as worried about the charge cycles. Tests 1 and 2 in the charge advancement showed that utilizing deterministic streamlining procedures to satisfy limited EV need the executives is attainable. The reenactment discoveries of investigation 3 demonstrate that the enhancement structure had the option to maintain the ideal charging period while obliging clients' EV accusing prerequisites of something like a 5% remuneration of their underlying charging necessity.

5. CONCLUSION

All in all the AI system for electric vehicle infrastructure (EVI) that has been proposed offers a careful strategy for upgrading charging and energy the board in shrewd lattice settings. The structure gives a calculated way to deal with investigate and enhance EV charging ways of behaving through the incorporation of five modules: gauge explainability, EV charge-request forecasting, EV information augmentation, charge-request profiling, and EV charge streamlining. The framework handles average issues including lopsided information, wrong readings, and request variance by using modern AI strategies like Gaussian combination models (GMM), multivariate relapse, and deterministic advancement. Experimental information supporting the handiness of the system in further developing energy proficiency and client experience comes from certifiable contextual analyses, such Caltech's Versatile Charging Organization (ACN). The discoveries show that the system upholds sustainable energy ways of behaving, settles on it simpler to make instructed conclusions about lattice the executives, and makes it more straightforward to make charging arrangements that are more viable. In light of everything, the proposed computerized reasoning system can possibly advance electric portability and aid in the shift to a more sustainable and clean energy future.

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