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Original Article

Analysis of Enhancing EV Charging Efficiency in the 5G enabled Smart Grid using Network Slicing, Edge Computing, and AI-based EV Charging Prediction

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Abstract - *As both electricity infrastructures and EVs have become more commonplace, there has been a lot of interest in vehicle-to-grid (V2G) technology as a possible energy management solution in the 5G smart grid. Due to EVs' high mobility and low reliability, the smart grid has a hard time keeping up with the demand for on-demand services. Since this is the case, we propose a new smart grid architecture for the 5G smart grid that incorporates network slicing and edge computing. We can improve the efficiency of EV charging and reduce costs for energy service providers by tracking the two-way traffic between EVs and smart grids. In order to maximize the effectiveness of EV scheduling, accurate predictions of EV charging behaviours are a significant problem for V2G systems. In this study, we provide a hybrid AI-based approach to estimating how often EV owners will plug into their vehicles. Simulation findings show that the proposed prediction system provides more accurate forecasts and more efficient scheduling for EV charging than existing leading methods.*

Keywords - *Electric Vehicle, Charging station, 5 G technology, Wireless communication, Energy.*

1. Introduction

Global demand for electric energy has significantly increased as a consequence of the impressive growth in electric vehicles (EVs). The market for electric vehicles worldwide has expanded dramatically. A few hundred EVs were on the road in 2010, but by 2017 there were over three million, and by the beginning of 2019, there were almost six million [1]. Providing alternatives to traditional vehicles are electric automobiles. Since the EV generates no carbon emissions during operation, it has the potential to lessen total climate impact and pollutant emissions significantly. The need for biofuels would decrease as fossil fuel use was gradually phased out. Compared to CVs, which have an efficiency of less than 20%, electric motors have an efficiency of between 80 and 95 percent [2]. As environmental pollution and the depletion of fossil fuels become greater concerns, electric vehicles (EVs) are gaining popularity. Electric vehicle uptake is lagging below projections. Electric vehicles have a hard time breaking into the market because of their short driving range and lengthy recharge times [3].

Despite having a high initial cost, electric vehicles are less expensive to maintain and use minimum energy than existing automobiles. Many research institutions and energy suppliers have started actively considering ways to lessen the strain on local electrical networks caused by the rising number of electric car charging stations as a result of the rapidly expanding EV demand and EV charging. The most efficient ways to address this issue for local electrical networks are renewable energy sources like wind and solar, which may also help the infrastructure for EV charging [4]. The growth of the electric car industry has made the building of charging infrastructure essential. Innovation in information and communication technology (ICT) for the automobile sector constitutes a crucial competency globally. The ICT sector in Romania makes a 13% contribution to GDP growth, an 11% increase in employment, and a significant contribution to developing a more responsive and dynamic energy market [5].

The industry's major goal is to provide consumers with automobiles that are more intelligent and connected. The need for innovation is growing daily, including questions about manufacturing, market trends, and driving safety and privacy. This article talks about the benefits of 5G technologies, which are present in all of the trends, and the challenges of applying them in light of the existing demands. The article also discusses the development of charging stations and their adjustments to intelligent features. It is worth noting that the efficacy of current charging stations will be greatly increased via the development and implementation of the smart charging station.

The most significant issues of 5G technology allow for very rapid user communication with increased capacity and high data rates. In contrast to 2G, 3G, and 4G, each successive generation of cellular technology has brought about modifications in frequency ranges and operating modes [6]. Every day, more electric vehicles are being used throughout the world to minimize carbon emissions from gasoline and diesel automobiles. In terms of available charge points, nearby charging stations, power, waiting periods for new cars, etc., synchronizing the charging stations with the electric vehicles is the main issue when developing electric charging stations for EVs. Efforts have been made to transform standard charging stations into smart charging stations based on 5G technology so that these problems may be studied.

Deep learning algorithms are widely recognized for their ability to forecast time series data, including network traffic and user behavior [7]. Researchers have been attempting to employ recurrent neural networks (RNNs), a crucial field of deep learning, to resolve the challenge of time series prediction in recent years. In terms of EV prediction, RNNs have been shown to outperform more traditional kinds of deep learning. It might be a representation of sequence or time-dependent phenomena such as speech recognition, financial markets, or online traffic [8]. However, Traditional RNN models cannot be disregarded because of their flaw in long-range dependencies that might result in gradient disappearances.

The most often used RNN variant, the long short-term memory (LSTM), is typically used to store long-term dependencies. Thus, LSTM is preferable for EV charging research. In [9], a recurrent neural network (RNN) based method is used to improve EV energy use through trajectory and delay prediction. However, the prediction accuracy of the previously mentioned studies cannot fulfill the requirements of EV charging behavior analysis in the 5G smart grid because of the complexity of user charging behavior and the large number of EVs.

This essay has five parts; the introduction discusses the requirements for intelligent charging stations, issues with electric vehicles, and the applications and limitations of 5G technology. Part 2 of the discussion covers the related work component related to wearable technology and 5G, as well as its applications and operational issues. The design of charging stations and how they may be used as smart charging stations is covered in Section 3. Section 4 offers implementation based on prior research and published literature. The findings and discussion are provided in section 5. Section 6 of this article presents the study's conclusions and suggestions.

2. Related Works

The future of technology, business, and scholarly study is the 5G network. This network has the ability to link and integrate all of the components, improving living quality, communication efficiency, and technological linkages. After sifting through data from a number of sources, we were able to put together a comprehensive picture of the 5G network from a number of different angles.

The popularity of electric vehicles is rising steadily in several nations throughout the globe. However, the lack of charging sites prevents EVs from being widely adopted by people throughout the globe. As the number of people using electric vehicles grows, more public charging stations are being installed. However, if EVs are charged utilizing the current fossil fuel-powered infrastructure, the distribution network and the environment will be negatively affected. Powering vehicles with renewable energy sources like solar photovoltaic (PV) panels and wind turbines would be ideal. It would also be an unwavering step toward a spotless natural setting. The charging station's electrical output may be insufficient or extremely high depending upon the available energy sources (such as renewable energy sources). Most sources agree that connecting Renewable energy conversion devices to the grid is feasible and cutting-edge.

An EV's battery SOC and the volume of EVs on the road are also pieces of information that ICSs may supply. 5G Cellular Vehicle to Everything (C-V2X) would dramatically improve connected EVs by facilitating near-instantaneous communication between cars, buildings, infrastructure, and charging stations. For the impending fifth generation (5G), it is necessary to put up sophisticated sensors and measuring systems with communication network backbones.

IWPT (intelligent wireless power transmission) using magnetic coupling or concept induction approach is used by Sultanbek et al. [10] to charge an electric car. The coils are automatically aligned using the fingerprint recognition technique. This collection offers various advantages, including improvements to begin smart charging during off-peak hours, energy savings, error reduction, cost reduction, and time savings.

Chen et al. [11] examine the spread of electric vehicles in various areas and nations. To determine how successful a strategy is, a PAM (path-based programming) model and a POM (point-based planning) model are developed using the SEM (strategic effectiveness assessment) paradigm. The purpose of this method was to meet both rapid and typical charging demands.

V2X (vehicle-to-everything) connections with infrastructure facilities and vulnerable people along the roadway are presented by Toghi et al. in [12]. The system was designed to boost performance, reduce system constraints, and forestall performance degradation. Future versions of all vehicles might use this technique. According to Corchero and Sanmarti [13], the electric vehicle's battery may be utilized for things outside, only supplying energy to the system. Analysis of the V2X (vehicle to everything) technology is done from an economic and environmental standpoint.

With the help of 5G, Lu et al. [14] provide a fresh viewpoint on enhanced services for pedestrians and drivers as well as a stronger link between vehicles and sensors. Low service latency, excellent dependability, wide communication coverage, and increased safety are just a few advantages of merging V2X (vehicle to everything) technology with 5G. They also examine the security, privacy, and trustworthiness of 5G V2V services. V2G (vehicle to grid) is a topic covered by Shen et al. in their discussion of EVs and IoT. The suggested design increases service quality and cost efficiency. This system's construction is based on how electric vehicles charge. Performance assessment and cross-validation tests were used to verify the approach. Sun et al.'s [16] proposal for a 5G smart grid exchanges data and offers a database for further study. They strive towards electric vehicle scheduling effectiveness. They examine the vehicle's various actions and develop a prediction method using artificial intelligence.

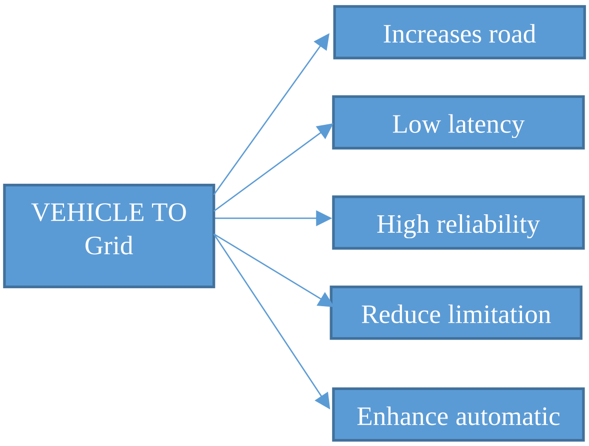


Fig. 2 Benefits of vehicle-to-grid connection using 5G

The research that has already been done on this subject was reviewed and briefly described in the paragraphs that followed.

Mallikarjuna et al. [17] offer a V2V system using ZigBee protocols. They created this system taking into account factors like poor reaction times, inaccurate distance measurements, incorrect speed calculations, etc. Vehicles will communicate with one another using location identification to determine their relative distance. For a military application, Abul Masrur et al. [18] provide a V2V and V2G. The system's many benefits include its quick formation time, effective power solution, integrated design, intelligence, and plug-and-play functionality.

The article details the process for enhancing fuel efficiency. All of the connections that a vehicle may have are covered by Liu et al. [19]. They provide insights, strategies, and procedures to strengthen the connections between the car and grid and the house. A predictive strategy for controlling the front wheel's steering angle is presented by Wei et al. in their study [20]. Elements like lateral and longitudinal orientations, string stability, safety, etc., are considered. This technique demonstrated flexibility and resilience in various driving scenarios through experiments and simulations.

Alrubaee [21] introduces V2X technology. He is focused on minimizing the potential for crashes to occur. Data transmission is made possible via the network connection, which also enables access to the internet and mobile networks. Deinlein et al. [22] provide the OMNeT++ framework 5G-Sim-V2I/N to present the connection with the network. This work claims that hundreds of digital vehicles were put through their paces over a variety of road conditions.

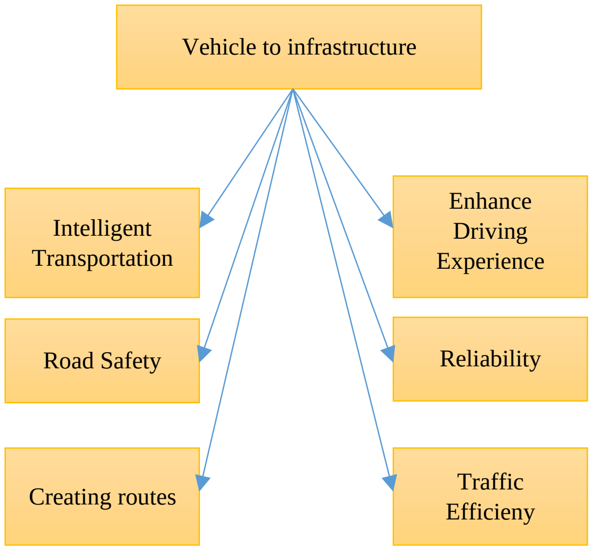


Fig. 3 Presents V2I (vehicle to infrastructure)

The discussion regarding CAN security on communication networks is introduced by Barletta et al. [23]. Their primary focus is employing a Kohonen SOM (self-organizing map) network to identify abnormalities and intrusions. They can compile a sizable database that aids in performance and efficiency enhancement.

All of the proposed linkages were created to enhance driving, promote connectivity, and boost pedestrian and other traffic participant safety. The ability to continuously communicate with the surroundings presents a fantastic potential to prevent crashes, lower accident rates, and enhance driving performance. The near future emphasises the need for modernization and social and consumer adaptation. Linking vehicles together has the potential to improve safety and security on the road greatly. Links between vehicles and pedestrians are important for maintaining public safety and tranquillity, as are links between vehicles and infrastructure for avoiding accidents and other mishaps. When discussing the means of connecting to a network, a fresh range of potential outcomes emerges databases, immediate information, programmed activities, road fluctuations, quick solutions, internet connection, mobile network, etc. The majority of the issues described above may be avoided by the driver with the aid of 5G implementation through V2N.

3. Network Architecture Design

This research proposes a network architecture for smart grids based on network slicing and edge computing, allowing for the abstraction or sharing of substrate resources. Infrastructure, control, and slice layers make up the suggested architecture's three tiers. Initially, the slice layer may provide whole slices of the smart grid infrastructure for billing purposes. In addition, the control layer may oversee the distribution of smart grid network resources to services according to their respective pricing tiers. Thirdly, EV users may have access to wireless resources through the infrastructure layer. This architecture ensures the seamless functioning of hybrid AI in real-time by augmenting edge computing's end-to-end processing capabilities and exceptionally high transmission speeds. This layer's charging stations serve as data collection points. The proposed hybrid AI algorithms have their physical foundation in the network architecture of smart grids, which is built on network slicing and edge computing.

Technologies based on coordinated control theory, distributed control, and billing services underpin the smart grid network architecture. The irregular or continual requirement for EV charging and charging information obtained from actual networks form the basis of the EV charging service. Network visualization, the OpenFlow protocol, and cross-layer control may be used to convey charging data. Power line communication (PLC) and wireless communication networks might enable data interchange between EVs and charging stations.

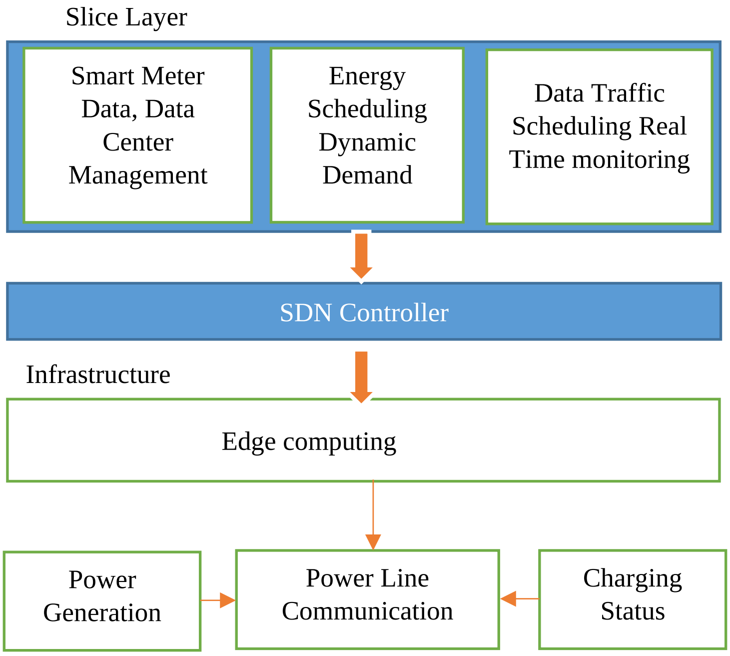


Fig. 4 Three-layer architecture of smart grid

The edge cloud saves and interprets the data on charging behavior obtained from EVs to enhance the charging schedule. The infrastructure layer may provide an interface via which electric vehicles (EVs) can communicate with the charging station, gather information about their charging habits, and transfer that information to the control layer. This layer bridges the gap between "slices" and "backbones." Requests to charge electric vehicles (EVs) might be handled at the control layer, together with optimization of the charging schedule and supervision of the V2G system as a whole. We specifically collect data on charging behavior from various sensors installed in EVs and charging stations. This information is compiled from various sources, including sensors inside the vehicle that reports on battery life, sensors on the roads and charging stations that report on how often electric vehicles are used, and user reports. Information about EV charging habits, such as remaining vehicle kilometers, charging station availability, and battery charge state, may be gleaned by the smart grid with the help of these broad data sources. Artificial intelligence algorithms can use all the charging data to evaluate and predict how EVs will charge.

After receiving the EVs' predictions for charging and their requests for charging services through the infrastructure layer's user interface, the controller will change the charging ID in the EV management system. The edge computing module receives requests for charging service through WSN when EVs attempt to approach the charging station. PLC and controller handle information exchange. The edge computing module receives data from EV sensors and battery sensors through vehicular WSN when the EVs are in motion. When there is a significant shift in EV-side charging service requirements, the charging station uploads this information to the V2G system over a multicast communication network. It changes the charging station's status in the system.

4. Working and Implementation

Predicting EV customers' charging habits is one approach to easing the strain on the power grid caused by EV charging. There is a broad distinction between daily and occasional EV drivers. The pricing patterns of frequent users may be fairly predicted, while occasional users' prices are unpredictable. The forecast of typical user charging behavior is helpful, but if user charging behavior becomes more erratic, the prediction error will increase. A year's worth of data from a single charging station is used as a training set for our purposes. User IDs, charging start and end times, disconnect times, total charges, and payment amounts are only some of the details recorded for each user. There are 26,000 user billing entries in the dataset.

We pre-process the data before clustering. First, we exclude people from the dataset who have less than three entries since we believe they are not local users. We select the standard deviations of the average charging time, the charging time, and the connection time as the clustering vector to help us distinguish between reliable and erratic users. We normalize the data using the linear normalization approach, as shown in Eq. (1).

$$X^* = (X - X_{min})/(X_{max} - X_{min}) \quad (1)$$

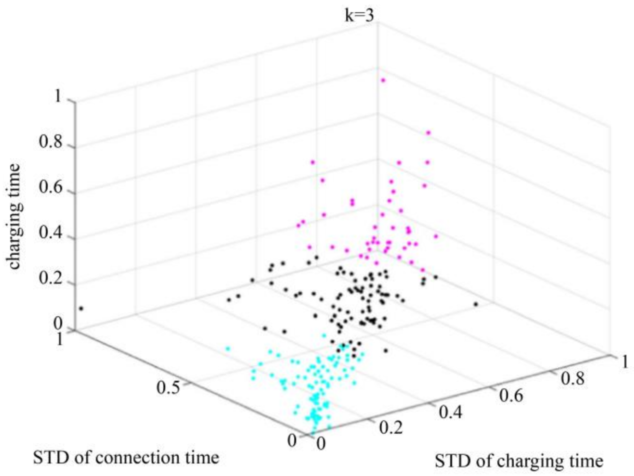
4.1. K-means-based EV Charging Behaviour

One unsupervised learning approach that works well for categorizing unlabeled data sets is K-means. The data may be separated into K clusters by it. The Euclidean distance is the most popular way to measure the separation between two vectors; however, there are other approaches as well.

The machine learning system categorizes people into three groups, as illustrated in Fig. Based on our data, we think consumers in the red and blue have predictable billing patterns since their standard deviation is minimal. On the other hand, certain consumers exhibit erratic charging behavior, which is identified in Fig. 4 as green patches. Due to the high standard deviation, such consumers are of little use in the centralized scheduling of the power system. As a result, we employ a hybrid artificial intelligence system to divide red, blue, and green people into different categories.

4.2. KNN-based EV Charging Classify

New users must be categorized when they sign up based on their activity. Reclusting the whole information each time a new EV uses the charging station is a significant issue, however. Therefore, based on previous clustering findings, we categorize new users using the k-nearest neighbors (KNN) approach. To categorize samples, supervised learning methods often utilize distance measures between unseen objects and known ones; one such method is called KNN.



Training samples may be selected from among the first K new objects, and those objects are then labelled according to the classification to which the greatest number of their closest neighbours also belong. The KNN method successfully categorised all the data points used in the study.

4.3. LSTM-based EV Charging

For its ability to recall a lengthy time sequence, the RNN algorithm is used to detect natural language. However, extending RNNs into ultra-deep structures highlights the gradient vanishing issue as the sequence length grows. Some RNNs with forget units were offered as solutions to the vanishing gradient issue, such as the LSTM and GRU. The memory cells might choose when to let go of specific charging information in this manner, allowing them to choose the ideal charging period.

5. Experiments and Results

As a data set for modelling, we utilize a charging station's one-year charging history in India. User IDs, charging start and end times, disconnect times, total charges, and payment amounts are only some of the details recorded for each user. 318 users' 26,000 billing records are included in the data collection. Through the application of the aforesaid hybrid artificial intelligence, we have separated EV consumers into regular and irregular users. While the charging habits of irregular users are unexpected, those of frequent users are predictable and consistent. In our experiment, we used an RNN with a single LSTM cell to analyze the data from the categorized EV users. Our proposed model's efficacy was then assessed by contrasting the expected user fee with the actual user charge. Additionally, we utilized the mean square error (MSE) as

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \quad (2)$$

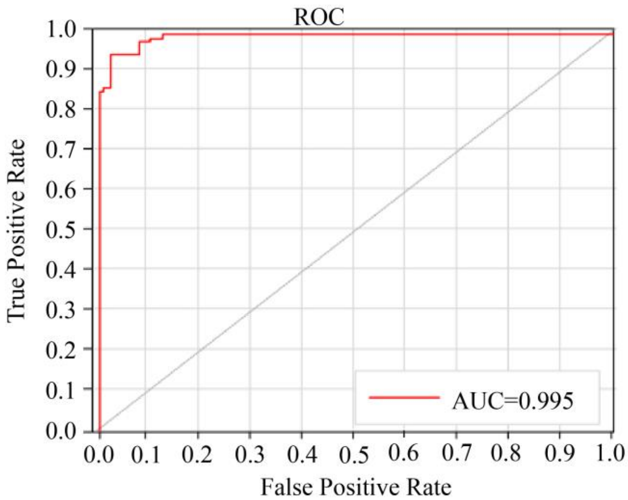


Fig. 6 RoC curve

In this experiment, we train and assess the efficacy of a hybrid AI-based prediction model. Figures 7 show the outcomes of the regular charging data predictions. The findings show that although irregular customers' charging behavior is hard to forecast, their estimated value is fairly comparable to the actual data.

Since the trial outcomes mostly match what we anticipated, our suggested strategy is successful. According to experimental findings, hybrid artificial intelligence performs well with normal charging data. In order to create the best power pricing, it is important to estimate the charging habits of frequent EV users. By taking this prediction into account, irregular EV charging data may be disregarded.

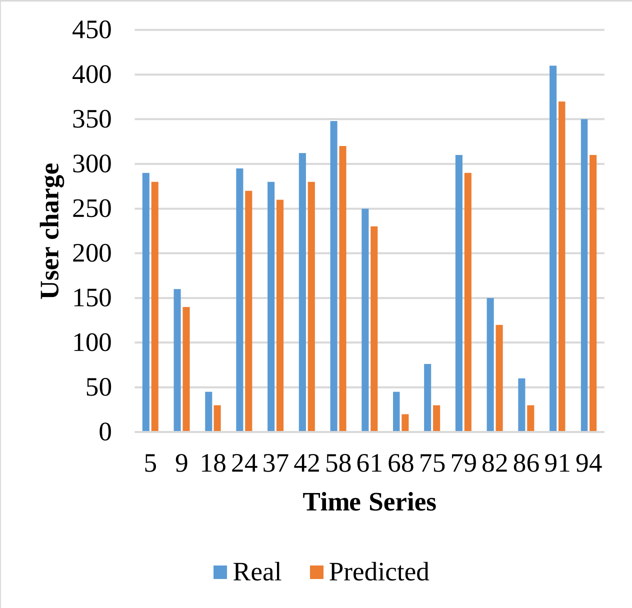


Fig. 7 Regular data for EV charging

6. Conclusion

Using a hybrid AI-based system for monitoring charging behaviours in the 5G smart grid, we can effectively provide on-demand charging services for EV customers. The EV-CBA system's two most ground-breaking features are its hybrid AI algorithm and novel three-layer smart grid design. The suggested smart grid network architecture can accommodate both the irregular and consistent EV charging needs of the 5G smart grid via the use of network slicing and edge computing. Hybrid AI algorithms may be easily integrated into pre-existing systems with the help of the material support provided by the proposed three-layer smart grid design. Accurate forecasts of future charging requirements are supplied by KNN-based EV charging behaviours classification is combined with LSTM-based EV charging in this hybrid AI system. The charging habits of electric vehicles may be better understood with the use of a multi-stage hybrid prediction method. The simulation results show that the proposed EV-CBA system is more accurate in predicting EV charging behaviours due to its improved clustering capacity and classification performance. The forecasts might be utilized for scheduling 5G smart grid charging for electric vehicles.

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