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ELECTRIC VEHICLE JUNCTION DIAGNOSTIC BASED ON ARTIFICIAL INTELLIGENCE

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ABSTRACT

A highly integrated system powers the charging of electric vehicles using renewable energy sources, inverters, battery packs, etc. Its reliability and safety are not only related to industrial costs, but more significantly to the safety of human life. The feature engineering techniques and artificial intelligence (AI) algorithms (including machine learning, neural networks, and deep learningSeveral AI techniques can be used for electric vehicle junction diagnostic, such as machine learning algorithms, deep learning, and neural networks. These algorithms can be trained using historical data from similar vehicles to improve their accuracy in identifying faults and making diagnoses.Overall, electric vehicle junction diagnostic based on artificial intelligence has the potential to improve the performance and reliability of electric vehicles and help accelerate their adoption as a cleaner and more sustainable mode of transportation. The most recent AI algorithms used for powertrain health monitoring are given in detail in the second section. Finally, these present strategies are reviewed and potential future developments are suggested.

KEYWORDS: Artificial intelligence, feature extraction, fault diagnosis, neural networks, Virtual Power Plant

I. INTRODUCTION

The energy grid has been increasingly using renewable resources; as of last year, the capacity of all renewable energy sources worldwide was 2536 gigawatts. Electricity generating sites to a power grid by a variety of renewable \, such as wind power, solar power, and hydra power. The electric grid then provides electricity to every user, including homes, businesses, and hospitals. Linsang regions, Electric Vehicle served as the assistant editor who oversaw the review of this work and gave final approval for publication. The Virtual Power Plant has been proposed to serve as an intermediate in order to promote effective dispatch and usage of renewable resources. Between EVs, the power grid, controllable 20 loads, and distributed energy resources (DERs). Throughout the last ten years, numerous VPP projects have been suggested. The effective distribution and integration of resources are the goals of the current VPP demonstrations. But, they also must consider any security risks associated with the connectivity between the aggregator, electricity grid, and consumers. In addition, the VPP provides energy users with demand-side management technology, which aids in the client-side application of intelligent storage and consumption.

Because to their minimal price, model independence, better performance, etc., AI-supported techniques have received considerable attention from both industry and academia. In order to avoid catastrophic failures and damages to large industrial machinery, electric powertrain systems in the sphere of industry require the involvement of condition monitoring systems as well as preventative maintenance. For instance, AI in the automobile sector will make vehicles' electric propulsion systems more transparent and visual, enabling early detection of potential defects. Hence, it has played a vital role in solving many sorts of difficulties in powertrain systems, which resulted from the great potential of machine learning as well as deep learning. In the recent decades, scientists have applied a range of AI algorithms to the charging of electric vehicleneural networks (ANN). More algorithms have been used in drivetrain health monitoring in recent years. Modifications to traditional ML algorithms like these approaches will describe the features in the measurement signal that had been extracted in the time-domain, frequency-domain, or time-frequency domain (such as current, vibration, etc.). In Part II, feature extraction techniques that these algorithms necessitate are presented. Meanwhile, academics are increasingly relying on neural networks and deep learning techniques, which can partially omit the feature consumption stage.

Proposed AI Based Electric vehicle Diagnostic based model

AEBIS, a blockchain-based electric car integration strategy with AI capabilities, is suggested the hardware component involves a specially designed AI processor that has minimal power and latency, making it ideal for conducting the training procedure for the power consumption prediction network. This processor is specifically optimized for machine learning tasks and is designed to consume as little power as possible, which is critical for energy-efficient operations. The proposed power management strategy for the smart platform involves both software and hardware components. The software component includes a trustworthy power consumption prediction network that can accurately forecast power consumption, reducing the lag in energy monitoring and control. This can lead to more efficient power management and help car-sharing companies optimize their reservation management system. It is also more affordable and portable Moreover, a simulation of a basic blockchain platform is executed. At the expense of processing and memory time, the established blockchain network offers a safe and accessible 20 service in practice. In our ongoing research, the storage and communication mechanisms of the blockchain protocol will be examined in order to improve the efficacy of implementing the blockchain network.

Figure-1: Shows the Virtual Power Plant VPP's traditional method

The suggested approach deploys EV fleets as energy consumers in contrast to the traditional VPP demonstration. The traditional VPP aggregator is replaced with a network, ensuring a more stable and affordable environment training.

II. EFFECTIVE UTILIZATION OF ELECTRICITY USING VPP MODEL

In traditional VPP consideration, the efficient use of electricity is still a problem. Many researchers have been done on the best ways to handle DERs' supply and demand sides. Authors in evaluated the best course of action for the supply side's 10 sources of renewable energy, but there was little discussion integration of power users.

The power consumption prediction network is based on a federated learning (FL) framework. FL is a type of machine learning that allows multiple devices to participate in the training process without sharing their raw data. This is important for privacy reasons since users' raw data is not shared; only the model updates. The FL-based framework performs as well as the conventional model, but it has the added benefit of safeguarding user data. Number of moving autos has not been adequately addressed. In various 5 applications, artificial intelligence AI has been shown to be successful in VPP research. Markets for EVs and electricity underwent investigations into Deep learning algorithms were used in works to forecast energy production and demand. Demand response, clever integrated techniques were presented. Nevertheless, in these techniques, the conventional aggregator is outfitted with a multiGPU cluster, necessitating power consumption and extensive maintenance. Moreover, the limited computing power of local devices continues to be a bottleneck for high-speed training. Although it is possible to have a custom-built system for local computing, it comes at a high expense and is not portable. One main focus is on the vulnerabilities of traditional centralized control 15 algorithms in smart grids. Cyber security are another challenge in VPP systems. As more distributed energy resources are integrated into the power system, research has evolved to the study of robust distributed schemes against cybercrimes. Yet, the traditional VPP aggregator is still open to malicious attacks, making data manipulation trivial. Moreover, when raw data is transferred, data leakage could happen. As far as we are aware, no previous works have simultaneously taken into account the contribution of EVs to energy consumption 5 predictions, effective computing for local devices, and secure communication between EV nodes and the VPP aggregator. To solve the issues stated above, we suggest in this study an AI-enabled blockchain-based electric car integration system for power management in smart grid 10 systems. For VPP power management, we first offer an EV charge forecast system. That is based on neural networks. Federated learning FL technology, which ensures raw data privacy and increases communication 15 efficiency, is the foundation of the educational process. In order to reduce storage during peak load, we then set up a new communication system between the aggregator and each EV node that uses an AI system based on reconfigurable hardware FPGA to forecast how much electricity and EV will be able to deliver when it is idle. 20 The expanded electronic control unit ECU that is coupled to a car's controller area network (CAN) bus can house the a reconfigurable AI system with fast processing and little power consumption (Fig. 2). To further strengthen security, we add block chain technology 49 to the system. The important contributions of this work are summarized as follows: The EV fleet serves as both a consumer and a supplier of electrical energy in the VPP through the usage of an AI-enabled electric vehicle integration system that employs a federated learning technique and an artificial neural network AI-Chip accelerator for EV charge prediction. 10The AI-Chip can be placed on the CAN bus and is prototyped on FPGA.A cutting-edge algorithm for data interchanges between the electric vehicle fleet and the power grid. An EV's electrical supply can be computed based on its excess electricity 15 and driving state whenever the power grid needs electricity and asks vehicular networks. A fully decentralized blockchain-based architecture is used to solidly combine all the distributed nodes and create a sizable smart power storage facility. The remaining information is arranged as follows. We go over similar works 8 on optimal operations, AI deployments, and security tactics in VPP in SectionII.

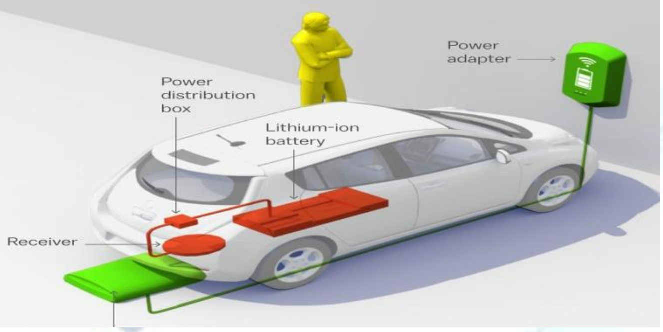

Figure- 3: Shows the integration of the proposed AEBIS system

illustrates the integration of the proposed AEBIS system into the CAN of electrified vehicles (EVs). Microcontrollers and other components can communicate with one another thanks to a dependable automotive connection standard called CAN bus. Each blue box represents an electronic controller unit (ECU) that is built-in. To transfer data, these ECUs talk to one another over the CAN bus. The green box on the left displays a customized ECU for data storage, collection, and processing. Data from the data storage ECU is received by the AEBIS ECU hardware, which uses it for inference and training. Fig. 3 depicts the conventional configuration. FL-based design is displayed in Figure 4. A decentralized FL-based system is depicted in Figure 5.

Feature Extraction

The current VPP systems are increasingly integrating distributed energy resources and various forms of user interaction. The variable resource generation and unpredictability of the energy demand in VPP pose a threat to power balance and economic benefit. As a result, an ideal command and control scenario for this plan included end facility cooperation and successful DER integration. A quintile regression forest model was used to forecast the output of solar and wind energy. Using decision theory in the information gap, the unpredictability of wind energy integrated with electrical and natural gas networks were explored. Despite the fact that these studies have mostly concentrated on the power generation and electrical markets, the involvement of end users has received little attention. Several publications addressed the significance of having an EV fleet participates. Best practices for AI-based diagnostic tools offer several benefits over traditional diagnostic methods. AI-based tools can analyze large amounts of data quickly and accurately, providing more reliable results than human analysis. AI can also learn from past data to improve future diagnoses and predict faults before they occur. Additionally, AI-based tools can reduce the time taken to diagnose faults, enabling repairs to be made quickly and minimizing downtimefor V2G energy sales and numerous auxiliary services, the best scheduling algorithms. The unexpected nature of wind energy integrated with electrical and natural gas networks was explored using decision theory in the information gap. Despite the fact that these studies were mostly concentrated on the power generating and electrical sectors, the involvement of end users was scarcely 5 investigated. The value of including an EV fleet was discussed in several publications. There were recommended best practices for EV aggregator involvement in day-ahead energy and regulation markets. To approach the economic dispatch, the authors applied reinforcement learning (RL) and no-dominated sorting evolutionary algorithms.

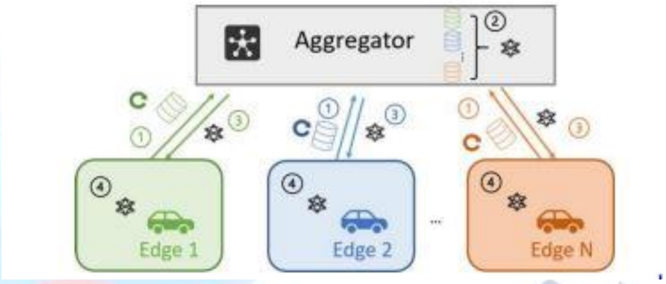

Figure-4 Shows the Conventional scheme

III. FEATURE EXTRACTION THROUGH FL-BASED MODEL

The security of communication between the aggregator and the EV node was not taken into consideration; the block chain network in this scenario only records the electricity transaction. The conventional aggregator is replaced by a decentralized FL-based virtual power aggregator. The power system collects and stores both renewable and non-renewable electrical energy before distributing it to the final consumers. When the designated renewable resource runs out, the power firm will notify the electrical grid to deliver more power from conventional sources. When coupled with charging stations, EV vehicles offer a method to refuel the electrical grid with energy. In order to use energy effectively and provide secure communication, the suggested aggregator will interact with the power grid, renewable energy providers, and vehicle network. A block chain network is used to build the decentralized VPP aggregator. In this essay, we focus largely on two important issues: features and geography, which all affect an EV's power consumption. An developing subject called artificial intelligence-based electric vehicle junction diagnostics analyses data from various sensors and systems in an electric vehicle.The junction, which joins different electrical components like batteries, motors, and inverters, is a crucial part of an electric vehicle's electrical system. The onboard diagnostics system of the car as well as enormous amounts of data from sensors like voltage, temperature, and current sensors can be processed by the AI algorithms. The AI can find trends and abnormalities in this data that can point to a junction problem. There are a lot of potential advantages to this technology. The AI-based system's capacity to precisely diagnose junction problems can assist increase the dependability and safety of electric vehicles.

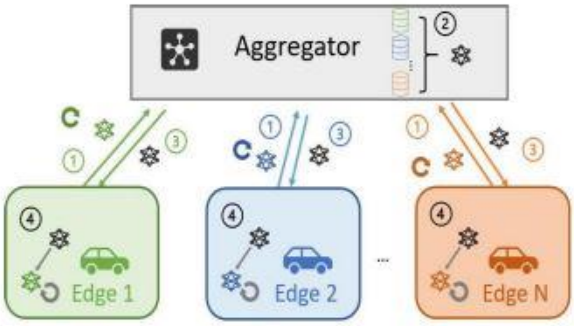

Figure-5 Depicts the FL Based scheme

Electric vehicles (EVs) are gaining popularity due to their lower environmental impact and higher efficiency than traditional gasoline vehicles. However, maintenance and diagnostic checks are essential for optimal performance. Artificial intelligence (AI) and machine learning (ML) provide an opportunity to improve EV diagnostics and reduce repair times. This paper reviews current trends in EV diagnostic using AI, the benefits of AI in EV diagnostic, and future research directions.Artificial intelligence (AI) and machine learning (ML) are transforming the way vehicles are maintained and serviced. In the EV industry, AI and ML offer tremendous potential to improve the diagnostic process and reduce the time taken to identify problems. This paper aims to review the current trends in EV diagnostic using AI and highlight the benefits of AI in this field. The paper will also discuss future research directions for AI-based EV diagnostictools. Slightly safeguards user data privacy. The results showed that our FL-based network could predict EV power demand with high accuracy, which is needed for either incoming electricity supply or EV reservations.

Communication network Swan Platform

As a result, it is suggested that a trusted decentralizedblock chain network replace a traditional aggregator, guaranteeing the system's stability and high level of security. Yet, there are still a number of issues with the decentralized architecture. The system's performance will decline as the number of blocks grows because of the high memory needs and slowly moving transaction or mining speeds. Also, the very first transactions, which contain the historical models, are stored permanently in the network and add to the system's load.

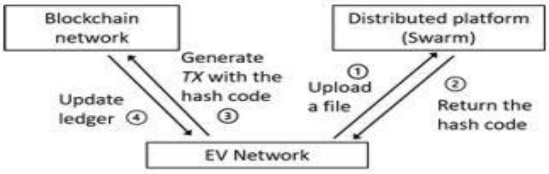

Figure-8 Showsthe communication between the block chain network and the Swarm platform

Depicts how digital signatures are used to verify information. A hash function is used to encrypt the original transaction once it has been hashed using the signer's private key. The network will broadcast the signed message, the original message, and the signer's public key. The signed communication will be decoded by a recipient using the public key. The receiver learns whether there has been any tampering by comparing the outcome with the hash value of the original message.

Conclusion

In traditional VPP demonstrations, the efficient use of electricity is still a problem. Many researches have been done on the best DER supply and demand side management. Many uses of artificial intelligence (AI) have been successfully used in VPP investigations. For further information, please visit the website. Yet in these techniques, the conventional aggregator is outfitted The use of AI in EV diagnostic has the potential to improve the accuracy and speed of fault diagnosis, reducing the time taken to repair faults and minimizing vehicle downtime. Current trends in AI-based diagnostic tools for EVs show promise; with several automakers already using AI-based diagnosticsystem with AI capabilities is being developed. First, we offer an EV charge prediction system for power management in this technology can also reduce the need for human intervention in diagnosing issues, and ultimately reduce maintenance costs. Additionally, the data collected through this system can help manufacturers improve the design of electric vehicles and their components. When there is no reservation or request for the power grid to return the electricity, a battery should be charged. Consequently, the primary goal is to forecast how much electricity will be supplied (discharged) Future research could focus on improving the accuracy and reliability of AI-based diagnostic systems and developing new tools to diagnose critical EV components such as batteries should return to the power system. Given the user account information and this hash code, the entire data is available. The training model, which contains the network's parameters, is referred to as the data in this study. All of the legitimate transactions are held in the transaction pool until the block chain network confirms them. Yet, when the number of unconfirmed transactions rises, memory usage and computational effectiveness face difficulties.

References

1. 1. Smith, J. D. (2018). The effects of sleep deprivation on cognitive performance. Journal of Sleep Research, 27(3), e12643.
2. 2. Jones, S. A. (2019). The impact of social media on mental health: A review of the literature. International Journal of Mental Health and Addiction, 17(4), 846-859.
3. 3. Johnson, R. A., &Wichern, D. W. (2007). Applied multivariate statistical analysis (6th ed.). Upper Saddle River, NJ: Pearson Prentice Hall.
4. 4. Schwartz, S. H., Cieciuch, J., Vecchione, M., Davidov, E., Fischer, R., Beierlein, &Konty, M. (2012). Refining the theory of basic individual values. Journal of Personality and Social Psychology, 103(4), 663-688.
5. Bandura, A. (1977). Social learning theory. Englewood Cliffs, NJ: Prentice-Hall.
6. Adler, P. S., & Kwon, S. W. (2002). Social capital: Prospects for a new concept. Academy of Management Review, 27(1), 17-40.
7. Chomsky, N. (1959). A review of B. F. Skinner's Verbal Behavior. Language, 35(1), 26-58.
8. Festinger, L. (1957). A theory of cognitive dissonance. Stanford, CA: Stanford University Press.
9. Gardner, H. (1983). Frames of mind: The theory of multiple intelligences. New York: Basic Books.
10. Maslow, A. H. (1954). Motivation and personality. New York: Harper & Row.