Intelligent Maintenance of Electric Vehicle Battery Charging Systems and Networks: Challenges and Opportunities

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ABSTRACT

Electric Vehicles (EVs) have become a trending topic in recent years due to the industry's race for competitive pricing as well as environmental awareness. These concerns have led to increased research into the development of both affordable and environmentally friendly EV technology. This paper aims to review EV-related issues beginning with the component level, through the system level, based on intelligent maintenance aspects. The paper will also clarify the existing gaps in practical applications and highlight the potential opportunities related to the current issues in EVs for the EV industry moving forward. More specifically, we will briefly start with an overview of the fast-growing EV market, showing the urgent demand for Prognostics and Health Management (PHM) applications in the EV industry. At the component level, the issues of the major components such as the motor, battery, and charging system in EVs are elaborated, and the relevant PHM research of these components is surveyed to show the development in the era of EV expansion. Moreover, the impact of an increasing number of EVs at the system level such as power distribution systems and power grid are explored to uncover possible research in the future.

The combination of existing PHM techniques and robust measurement or feature extraction methods can provide better solutions to address the motor, battery, or transformer issues at the component level. A comprehensive optimization and cybersecurity strategy will help to address the issues of the whole network at a system level. Four aspects of vision in the overall charging network – battery innovation, charging optimization, infrastructure evolution, and sustainability – that cover the demands of research in new battery materials, innovative charging techniques, new architectures of the charging network, and reliable waste treatment mechanisms are outlined. A conclusion is reached in this paper by summarizing the opportunities for future EV research and development.

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1. INTRODUCTION

The world is facing gradual deterioration from global warming due to a great amount of greenhouse gas (GHG) emissions by the extensive use of fossil fuels, especially from vehicle operation. Besides, the automobile industry suffers a setback due to the increasing crude oil price, which boosts the demand to develop the alternative to conventional vehicles. To address this issue, the implementation of electric vehicles (EVs) has attracted huge attention and is trending due to the promising characteristics of GHG emission reduction and power efficiency in recent years (*All-Electric Vehicles*, n.d.; *Alternative Fuels Data Center: Emissions from Hybrid and Plug-In Electric Vehicles*, n.d.). Although the EV cost is still higher than that of conventional vehicles, it becomes relatively competitive with the support from the government incentives and the decreasing cost of an EV battery. In fact, according to the working survey, the EV initial cost parity is coming within 5 to 10 years (*Update on Electric Vehicle Costs in the United States through 2030 | International Council on Clean Transportation*, 2021). Owing to the abovementioned benefits of EVs, the EV market has experienced substantial growth with the increasing demand for energy all over the world. Compared with the rapid growth of EVs, the PHM of EV and charging systems are lagging. Battery PHM has been widely studied. However, apart from the battery, the charging-related PHM is still

Table 1. Charging standards and application

Charge Station / Pile	Description	Equipment Supplier (*EV Charging Statistics – EVAdoption*, n.d.)
Level 1 AC	Voltage: 120 V (Deb et al., 2017) Charging Period: 4 – 13 hours (Brenna et al., 2020; Deb et al., 2017) Usage: Residential Area Advantages • wired (higher charging efficiency) (Sun et al., 2017) • charging can occur in off-peak times (overnight) (Sun et al., 2017) • bidirectional charging (Ghavami & Singh, 2017) Limitations: • home appliance malfunction can reduce available charge voltage (Sun et al., 2017)	Opconnect ChargePoint Greenlots Unaffiliated
Level 2 AC	Voltage: 240 V (Deb et al., 2017) Charging Period: 1 – 4 hours (Brenna et al., 2020; Deb et al., 2017; Sun et al., 2017) Usage: Parking Lot Advantages • wired (higher charging efficiency) (Sun et al., 2017) • charging can occur while the car is parked for shorter periods to replenish battery capacity (Sun et al., 2017) • bidirectional charging (Ghavami & Singh, 2017) Limitations • limited availability for many users (Sun et al., 2017)	ChargePoint Tesla Blink Network SemaConnect Network EVgo Greenlots Opconnect AeroVironment Network EVConnect
Level 1 DC	Voltage: 208 V (Deb et al., 2017) Charging Period: 20 minutes for 50% (Sanguesa et al., 2021), 30 minutes for 80% (Brenna et al., 2020; Sanguesa et al., 2021; Sun et al., 2017), generally 0.5-1.5 hours (Deb et al., 2017) Usage: Charging Stations Advantages • wired (higher charging efficiency) (Sun et al., 2017) • quickest charge to extend range/act in place of fueling station for standard vehicles (Sun et al., 2017) Limitations • high stress on power supply system, susceptible to outages (Sun et al., 2017)	ChargePoint Tesla Blink Network Network EVgo Greenlots Opconnect AeroVironment Network EVConnect

challenging due to the diversity of environment, equipment, driving behavior, and other factors. Taking the whole charging network into consideration, there are still some challenges existing at different levels:

- At the component level:

The current PHM technology is more likely to focus on the individual important components in the EV and its charging networks such as the battery, motor, or transformer in the power grid. The PHM technology of the charging system or pile is less discussed.

- At the system level:

A comprehensive maintenance strategy for a charging network that can interact with EVs does not exist. Most research of charging networks focuses on several specific aspects, including cybersecurity, location optimization of charging piles, and power impact on the power grid.

This paper aims to review the existing practices to address the above-mentioned challenges and discuss the PHM research and development opportunities in the era of EV expansion. This paper outlines the PHM opportunities from the following aspects:

- PHM for EV components like batteries, onboard charging devices, and motors
- EV charging network

The remainder of this paper is organized as follows: Section 2 introduces the overall EV charging network and the corresponding challenge of crucial components. Section 3 details the opportunity of EV research and explores the application. Section 4 demonstrates the future vision of EV research. The conclusion is given in section 5.

2. OVERVIEW OF EV CHARGING NETWORK

The entire EV network can be viewed as the interaction between the EV and the charging system. The illustration of the charging network is shown in Figure **1**. The charging network transmits the energy from a power plant through the transmission line, connecting the power distribution network to the application network. When EV is connected to the charging device, the corresponding charging mechanism will be activated. The different charging scenarios of EVs can be roughly divided into three applications: residential, parking lots (commercial areas), and charging stations. All applications can be equipped with a smart meter (SM) to enable bidirectional communication between EVs and the power grid. Hence, EVs can upload information such as state of charge (SoC) and state of health (SoH) through the SM, which can then allow the operation to be controlled by the SM based upon dynamic pricing or electricity loading of the power grid. Moreover, the EV user can decide their preferred location for charging based on the information given through the vehicle's communication system and entire network.

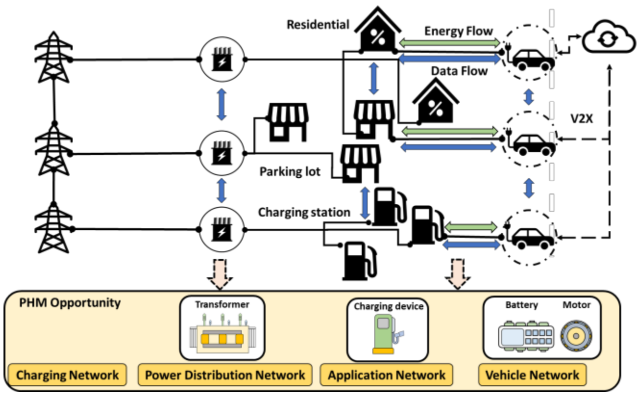

Figure 1. The structure of an EV charging network

Currently, three major charging standards, SAE-J1772, GB/T 20234, and IEC-62196 have been developed for different regions (Sanguesa et al., 2021). More specifically, SAE-J1772 has been adopted by North America and the Pacific zone. However, IEC-62196 is used in Europe while the GB/T 20234 standard is developed and used in China. The specifications, the corresponding applications, and equipment suppliers of these standards are summarized in Table 1. Based on the abovementioned applications, the charging systems can be divided into three levels. Level 1 AC refers to residential usage. The longest charging time and lower charging voltage (120V) are suitable for household and off-peak period charging. The main limitation of this level is that a home appliance malfunction can reduce available charge voltage. At level 2 AC, the faster-charging speed and higher charging voltage (240V) are used in commercial areas such as parking lots. The main limitation is that it is only available to a limited number of users. At level 1 DC, the fastest charging speed acts in place of a fueling station for conventional vehicles. At this level, it allows for charging the battery to a certain percentage in a short time. However, the simultaneous charging of mass EVs could lead to high stress on the load of the power grid.

In the charging network, the power grid and transformer are the major components. The reliability of power delivered to the customer has received attention in recent years, especially considering the impact on customer satisfaction. The current major issues and existing solutions from the transformer and power distribution have been summarized in Table 2. The power transformer is a passive component used for converting the AC voltage or the circuit isolation with separate coils. The high amount of energy required from charging EVs in bulk can put the transformer at risk of overloading. Moreover, the uncoordinated charging accelerates the component degradation of the transformer due to aging and overheating. On the other hand, the power grid also has several issues that need to be addressed, such as a mechanical fault or unstable voltage. All these issues combine to make the power quality worse and more unstable.

The battery is one of the most important components in the EV. The overall performance of the EV battery has a significant impact on both the EV itself and also the architecture of the charging networks. The commercial EV battery in the market is shown in Table 3. With the different combinations of battery chemistry, the characteristics of EV batteries have a significant gap between manufacturers. Based on Table 3, several observations can be made, including:

1. From a performance point of view, the overall performance of C-NCA or Si/Six-C-NCA produced by Panasonic and adopted by Tesla significantly outperforms other types of commercial batteries. However, the increasing demand for Cobalt makes the battery cost difficult to reduce. Moreover, the safety issues associated with this kind of battery limit the application. Due to these safety issues, EV manufacturers tend to choose other types of commercial batteries (such as LFP), or instead, try to develop new types of batteries (such as a semi-solid battery).

Table 2. Major Component of Power Distribution System

	Major Issues	Existing Solutions
Power Distribution Equipment (Transformers)	• Limited transformer capacity; EVs can more than double peak residential demand (Shuvo & Yilmaz, 2020; Wei et al., 2021) Aging and overheating, commonly due to the breakdown of insulating oil (Shuvo & Yilmaz, 2020), especially for uncoordinated charging (Deb et al., 2017)	• As transformers are replaced for regular aging, they will be more equipped in the future to handle the loads (Shuvo & Yilmaz, 2020) • Predictive maintenance methods proposed to mitigate losses due to incapable transformers (Shuvo & Yilmaz, 2020) • Supplement the power grid with the EVs (Deb et al., 2017)
Power Grid Stability	• Mechanical faults; thermal runaway (insulated soil), wear and tear – underground cables (Labrador Rivas & Abrão, 2020) • Natural causes (thunderstorms, icing) and accidents – overhead lines (Labrador Rivas & Abrão, 2020) • The limited voltage or voltage surge (Wei et al., 2021) • Power outage (Wei et al., 2021)	• Protective devices isolate fault from the rest of the system (Labrador Rivas & Abrão, 2020) • Supplement the power grid with the EVs (Deb et al., 2017)

Table 3. Overview of Lithium-ion Batteries for EVs

Type (Chemistry Combination)		Cell Characteristics				Battery size and range		Application	
Anode	Cathode	Capacity (Ah)	Voltage (V)	Specific Energy (Wh/kg)	Energy Density (Wh/l)	Energy (kWh)	Range (km)	Manufacture	Model
C	LMO-NMC	16~63	3.65~3.7	109~172	218~312	16~35.5	140	• Li-Energy Japan • Samsung SDI • LG Chem	• Mitsubishi i-MIEV (2008) • Fiat 500e (2013) • Ford Focus EV (2012) • Renault Zoe (2012)
LTO	NMC	20	2.3	89	200	20	130	• Toshiba	• Honda Fit EV (2013)
C	LMO-NCA-NMC	37-94	3.7	122~189	228~357	22~36	130~300	• Samsung SDI	• BMW i3 (2014, 2017) • VW eGolf (2016)
C	NMC	25-59	3.65~3.7	152~241	215~466	17~60	145~400	• Panasonic/Sanyo • Li-Tec • SK Innovation • LG Chem	• VW e-Golf (2015) • Smart Fortwo (2013) • Kia Soul EV (2014) • Chevrolet Bolt (2016) • Renault Zoe (2017)
C	LMO-NCA	33-40	3.75	155~167	309~375	24~30	135~172	• AESC	• Nissan Leaf (2010, 2015)
C	LFP	20	3.3	131	247	21	130	• A123	• Chevrolet Spark EV (2012)
C	NCA	3.2	3.6	236	673	60~100	330~500	• Panasonic	• Tesla S (2012)
Si/SiOx-C	NCA	3.4~4.75	3.6	236~260	673-683	60~100	330~630	• Panasonic	• Tesla 3 (2017) • Tesla X (2015)

2. Most selected chemistry material in the anode is synthetic or artificial graphite, except lithium titanate oxide (LTO) and Si-based material. Due to the low voltage and high-power capacity, the LTO-based cell is more suitable for electric buses. A Si-based cell is a carbon anode mixed with a small amount of silicon that can improve the cell energy.

3. As the capacity of the battery increases, the charging time of the battery will become longer. It may have a bad influence on user's purchase intention. Also, the corresponding fast-charging standard should be developed.

4. The variety of EV batteries shows that there is still no optimal solution for the current market.

3. PHM OPPORTUNITY

3.1. EV's Major Components

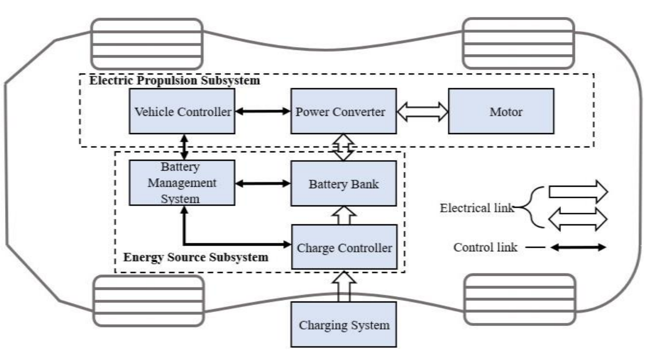

Figure 2. The major components of an EV system

To give a better idea of the crucial components in the EV system, a typical electric vehicle (EV) system is shown in Figure 2. There are two major subsystems: Energy Source Subsystem (ESS) and Electric Propulsion Subsystem (EPS). The critical components of the ESS include a charge controller, battery bank, and battery management system. The major components of EPS are comprised of a vehicle controller, power converter, and motor. A charging system is also considered because the operational activity of a PEV is impacted by the reliability of a charge station.

However, the importance of these components is not clear or not identified. From the reliability aspect, these components are different. A comprehensive study of the reliability, availability, and maintainability (RAM) of the vehicle framework has been conducted to assist in distinguishing the failure-prone components in the design (Talukdar & Deka, 2021). The RAM of a PEV system mainly fits Markov mathematical model to incorporate the characteristics of all components to estimate the UP (Operable) and DOWN (Failed) states. This case study (Talukdar & Deka, 2021), provides the reliability data for PEV that shows the failure rate of different components per year. On the other hand, technical reports (Fries et al., n.d.; *Update on Electric Vehicle Costs in the United States through 2030 | International Council on Clean Transportation*, 2021) use the Chevy Bolt EV as an example to predict the costs of common EV components in 2025, as shown in Table 4. Moreover, the cost of the charging system in Table 4 comes from the average cost both in California and outside of California based on one charger per site for the specification of a Level 2 public and workplace charger, which can be found in the literature (Nicholas, n.d.). Combining the abovementioned research,

Table 4. Chevy Bolt EV's major components

Component	Number of failures (per vehicle per year)	Cost Prediction for 2025	Function
Charge controller	2.70	$205	Charges the battery pack to convert AC to DC
Battery bank	2.72	$8000	Entire battery pack
Battery management system	5.93	$200	Keeps the battery's operating temperature within an optimal range
Power converter	4.58	$523	Converts DC to 3-phase AC for the e-motor
Motor	6.66	$1080	150kW permanent-magnet e-motor
Vehicle controller	5.57	$46	Communicates between the vehicle and charger
Charging system	21.9	$1174	Level 2 on one charger for public and workplace

Figure 3 shows a four-quadrant chart of the number of failures per vehicle per year and costs for major EV components based on the values of Table 4. The dotted lines used to cut the entire space into four different quadrants are set at USD1000 to mirror the anticipated annual EV maintenance costs listed in (Dodds, 2020) and 10 failures per vehicle per year. Both the charging system in the first quadrant and the motor and battery bank in the fourth quadrant will be discussed in the following sections.

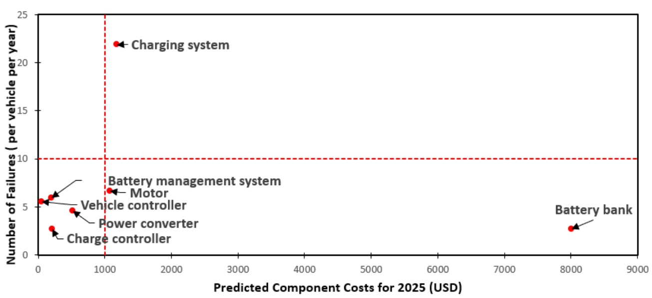

Figure 3. Four-quadrant chart of major components in EV

3.1.1. Motor

EV motors are mainly divided into five types: DC motors (DC), Permanent Magnet Brushless DC motors (PM BLDCs), Induction motors (IM), Permanent Magnet motors (PM), and Switched Reluctance motors (SRM). As an example in commercial EVs, conventional IMs are adopted by the Tesla Model S and Model X. The Tesla Model 3 adopts an SRM with internal permanent magnets (IPM-SRM). The Tesla Model 3 also developed dual-motor versions–an IM in the front and an IPM-SRM in the back. Permanent magnet synchronous motors (PMSM) are used by GM Chevrolet Bolt, Toyota Prius, Nissan Leaf, and BMW i3. Researchers survey that IMs are most commonly used, especially in India's EV market (Gundewar & Kane, 2022). The IM is easily exposed to various kinds of faults due to its continuous operation and variable load. Thus, condition monitoring of an IM becomes important for avoiding severe failure. There are two types of faults in the IM: mechanical faults and electrical faults. Mechanical faults include bearing, eccentric rotor, and unbalanced rotor that can be measured with vibration monitoring, while electrical faults include rotor bar and stator winding that can be measured with motor current signature analysis. The vibration and current sensors all extract the signals in the time domain. However, the signals are more sensitive to noise interference that may affect the effectiveness, so condition monitoring will be adopted for on-board diagnosis using the EV's startup or idle condition which can measure useful statistical features such as mean, root mean square, standard deviation, kurtosis, skewness, and higher statistical moments…etc. These statistical features can be effectively compared with the normal features to distinguish faults. Moreover, these features can be utilized in the artificial intelligence algorithms to diagnose the IM faults, as shown in Table 5.

3.1.2. Battery Pack

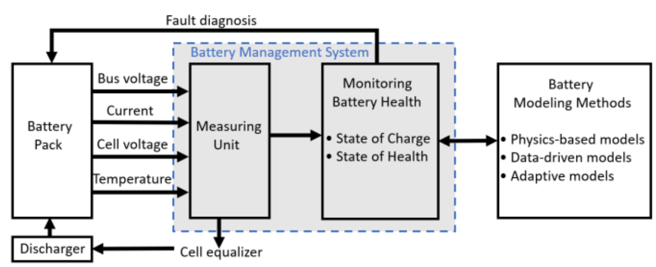

Figure 4. The architecture of the monitoring system in EV

As battery packs account for the most cost, effectively evaluating their reliability is an extremely important topic.

Table 5. Condition monitoring for the Induction Motor

Faults	Types	Monitoring technique	Fault diagnosis
Mechanical faults	Bearing	Vibration monitoring	Maximum correlated kurtosis deconvolution and improved empirical wavelet transform (Z. Li et al., 2019)
	Eccentric rotor		Artificial neural networks by statistical features (Gupta & Singh, 2019)
	Unbalanced rotor		Support vector machines (Pinheiro et al., 2019)
Electrical faults	Rotor bar	Motor current signature analysis	Modulation signal bispectrum analysis (Gu et al., 2015)
	Stator winding		Spectral analysis of instantaneous square stator current (Pires et al., 2015)

Table 6. Battery prognostics technologies

Methods	Models	Algorithms
Physics-based models	Thevenin model	Combine a series of RC circuits to provide the availability of predicting response at different timespan (He et al., 2012)
	Runtime-based electrical model	Design sophisticated circuits to model battery runtime and DC voltage response with a constant discharge current (*Using PSpice to Simulate the Discharge Behavior of Common Batteries | PSpice*, n.d.)
	Combined electric model	Acquire the dynamic characteristics of a battery to predict runtime and I-V performance (Chen & Rincon-Mora, 2006)
		Use non-linear squares methods to achieve online prediction of RUL (Downey et al., 2019)
Data-driven models	Machine learning model	Support vector machines algorithm considers temperature change, SoC, and C-rate to estimate battery SoH (Nuhic et al., 2013)
		Use SVM to estimate the SoC of a LiFePO4 battery cell (Álvarez Antón et al., 2013)
	Deep learning model	A deep neural network algorithm predicts the SoH and RUL (Khumprom & Yodo, 2019)
		Investigate FNN, CNN, and LSTM algorithms to explain the battery characteristics (Kaur et al., 2021)
Adaptive models	Sliding mode observer	The fast-paced and the slow-paced time-varying observers estimate parameters of SoC, SoH, terminal voltage, and polarization effects (I.-S. Kim, 2010)
		Propose a super-twisting sliding mode observer to estimate SoC (Huangfu et al., 2018)
	Kalman filter	A neural network combines Kalman filter for short and long-term SoC estimation (Bai et al., 2014)
		Estimate the battery model error: open circuit voltage drift and voltage sensor drift (Wang & Mu, 2019)

An effective Battery Management System (BMS) in EVs plays an important role. Not only does the BMS measure the voltage, current, and temperature signals of the battery pack to ensure vehicle safety, but it also estimates the state of battery health by using modeling methods designed to give feedback on fault diagnosis and the evaluation of battery life.

Figure 4 shows the schematic diagram of a BMS. Battery prognosis is normally performed in a controlled environment under optimal settings. However, lithium-ion batteries in EVs are highly sensitive to changes in operating conditions, especially the temperature, terminal voltage, and charge-discharge rates among others. Varying operation conditions will affect the performance and life of batteries and lead to potential failures. The estimation of SoC and SoH of batteries can be an indicator of battery health and how to keep the battery pack safe and reliable (Hannan et al., 2017; Sarmah et al., 2019). Determining the health of the battery pack can be decided by monitoring two key performance characteristics: the battery's impedance parameters and capacity parameters. Since these characteristics are a function of the internal reactions of a battery, they become difficult to monitor. Therefore, there are three common methods of monitoring modes: physics-based, data-driven, and adaptive modeling, as shown in Table 6.

Among the models, electrochemical and equivalent circuit methods fulfill performance well but cannot be straightforwardly applied to different batteries. At the same time, although data-driven models are effectively adjustable to the different types of batteries, obtaining the compelling and precise technique to estimate SoC and SoH is still a difficult task. To address this practical issue, the nondestructive test (NDT) methods, such as those used by X-ray, ultrasound, or infrared, to investigate SoC and SoH can be regarded as a solution. For example, reversible and irreversible thickness changes of lithium-ion pouch cells can be measured by laser scanning to estimate the aging degradation (Sturm et al., 2017). Therefore, the combination of NDT methods with supervised learning algorithms can construct a model that becomes a reliable battery management system. Apart from the research topic on the combination of NDT methods and current PHM techniques, the SoC and SoH prediction on a battery due to real driving cycles is another research direction (Cui et al., 2022; Hong et al., 2021). There are some new public EV battery datasets related to the practical driving pattern that are promising for future studies (Pozzato et al., 2022; Steinstraeter, 2020).

3.1.3. Charging System

With the rapid promotion of the electric vehicle market, the maintenance of the charging system is also a critical issue. One of the main issues is that most charging systems are installed outdoors and are therefore sensitive to environmental factors (e.g., rain and dew) that reduce the reliability of the charging components. Another central problem involved with charging an electric vehicle is the connector. The J1772 standard (Sanguesa et al., 2021) of the connectors was proposed by the Japanese and American markets, while European EVs utilize connectors based on the IEC-62196. Although these business markets are separate, it can still cause inconvenience for users who need to purchase adapters, subsequently expanding the expense and safety risks. Another important issue is to develop feasible fault diagnosis methods for the charging system. Since the charging system is connected by a high-power electric infrastructure that also needs to give stable electric power output to the vehicle, fault diagnosis methods become critically important. For example, researchers investigated 8 kinds of fault states: communication problems between vehicles and charging systems, insulation problems, output overvoltage of charging module, over-temperature, input phase loss, over-current, over-voltage of DC bus output, and contractor of DC bus output (Gao & Lin, 2021). Operating data can be collected during the operation of the charging system, and data-driven methods (e.g., Deep Learning algorithms) can effectively perform fault diagnosis of the charging system by analyzing operating data and extracting salient features.

3.2. Charging Networks

3.2.1. Cybersecurity

For the EV charging network, cybersecurity is one of the most important factors (Acharya et al., 2020; Sanghvi & Markel, 2021). Cybersecurity concerns with the charging network include data acquisition and transfer, control of devices, and network security challenges like attacks, intrusion, and so on. The cyberattack is the most direct method to examine the vulnerability of the charging network and can be categorized via the Spoofing, Tampering, Repudiation, Information Disclosure, DoS, and Elevation of Privilege (STRIDE) threat model (Acharya et al., 2020; kexugit, n.d.). Efficient detection and diagnosis techniques in the existing PHM technology would help to fix these issues in the charging network (Aiyanyo et al., 2020; Evans et al., 2013). Besides, a co-simulation platform is developed for analyzing the cybersecurity vulnerability of charging networks (Sanghvi & Markel, 2021). With the aid of this platform, more maintenance and defensive strategies can be studied in the future.

3.2.2. Transformer fault and degradation

The power distribution system is a subsystem of the entire charging network and is composed of basic power components such as transformers, transmission lines, and loads. Among these components, the transformer is a relatively sophisticated piece of equipment needed to guarantee the power quality of usage. The common transformer fault can be mainly categorized into several factors including insulation, winding, bushing, and tap changer. These factors account for more than 85% of the failure rate (Murugan & Ramasamy, 2019). These faults and the corresponding solutions can be found in the literature (de Faria et al., 2015). Moreover, at a system level, the fault location and cause are also important. Consequently, efficient PHM methods are crucial for the safety and secure operation of the system.

3.2.3. EV impact on power distribution systems

Although current EV charging research mainly focuses on smart charging methods used to optimize the start time and charging rate, the demand for the simultaneous and higher power output is expected to increase as the deployment of EVs continues to grow and adds more stress on various distribution systems due to uncoordinated charging (Akhavan-Rezai et al., 2012; Gilleran et al., 2021). The main impacts are overload on transformers, unstable voltage profile, and unbalanced load. Some optimization strategies have been covered by considering uncoordinated charging and coordinated charging (Akhavan-Rezai et al., 2012).

3.2.4. Fault location detection and diagnosis of power distribution systems

There are two types of faults encountered in the distribution systems: series and shunt faults (Gururajapathy et al., 2017). Series faults refer to the situation of unbalanced impedance existing on a line. Such faults can be judged by the frequency, rising voltage, and reduced current. On the other hand, a shunt fault is the general issue in the power distribution system, which can be found by an increase in current and a drop in voltage and frequency. In conventional fault location techniques, three fault detection techniques, traveling wave, impedance-based methods, and synchronized voltage and current measurement methods (Ajenikoko & Sangotola, 2016; *Analysis of Faulted Power Systems | IEEE EBooks | IEEE Xplore*, n.d.; Brahma, 2011; Lopes et al., 2015), are found in the literature. Due to the complexity of power systems and various uncertainty factors not considered in the conventional methods, data-driven methods are proposed by considering more information from feeder measurement, substations, and switch status. Some AI-based methods like artificial neural network, support vector machine, fuzzy logic, genetic algorithms, and pattern match approaches can be found in the literature (Aslan, 2012; Awalin et al., 2012; Y. Li et al., 2012; Salat & Osowski, 2004; Swetapadma & Yadav, 2015).

3.3. Conceptual Application

With all mentioned research topics in the previous sections, we propose a conceptual application based on the federated learning architecture shown in Figure 5. According to federated learning (McMahan et al., 2016), global models can be regarded as the server side, and electric vehicles and charging stations belong to the node side. On the node side, the charging station can collect the data, such as charging price, battery specification, charging status, charging location, and charging frequency, and upload it to global models for model training. However, if the electric vehicle itself wants to directly transmit data, such as users' driving patterns and battery estimation, to the server side, it will involve the issue of personal data privacy. The feasible way to circumvent this is to transmit the data of the electric vehicle to the driver's own mobile platform, which can train the model with the data. After the training model is completed, only the parameters of the model transmit to the global models on the server side (Melis et al., 2018). Global models adjust the model and pass updated parameters back to the mobile platform for model optimization. At the same time, there is an action of encrypting data in the process of data transmission of both mobile platforms and charging stations. This mechanism prevents anonymous attacks (Shafahi et al., 2018) from intercepting the data. When global models train a usable model, there will be many practical applications. For example, the charging price and the current idle status of the charging station are updated in real-time, so that users will get instant feedback. Users can also adjust driving behavior and know the health status of the EV battery according to the feedback from the global models. Moreover, the driver's route and the current battery status are also very important indicators. The local models can provide the driver with options to optimally reach the destination based on the remaining useful life of the battery. On the other side, when a new battery needs to be evaluated for consumption, it can be verified based on the previous training model of the same brand.

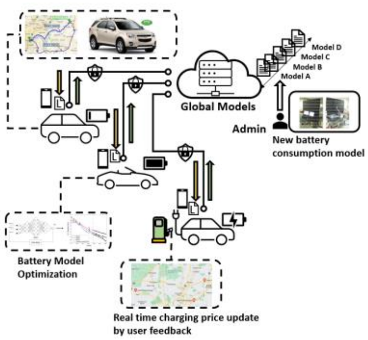

Figure 5. The architecture of conceptual application

4. FUTURE VISION

Although we have seen significant advancement and evolution of EV technology in the last decades, some aspects of the current technology still require further exploration and research to identify new solutions. Here we propose four aspects toward the different critical components in the EV charging network as shown in Figure 6.

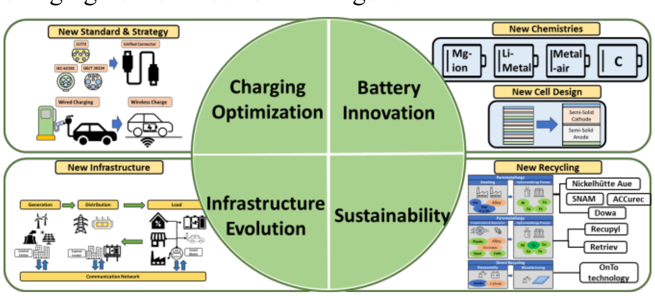

Figure 6. Four aspects of future vision

4.1. Battery Innovation

The battery is considered the most important component of EVs and also accounts for at least one-third of the total cost (Deng et al., 2020) associated with EVs. The battery has a direct impact on the overall autonomy of EVs. Due to its importance, the evolution of new batteries can further accelerate the deployment of EVs throughout the world. Below are several new battery evolutions that are currently being researched:

a. Magnesium-ion: This kind of battery replaces lithium with magnesium. It is expected that the magnesium-ion battery has a theoretical 3.2 kWh/L energy density and 1.7 kWh/kg specific energy (Zhirong & Maximilian, 2017).

b. Lithium-metal: In lithium-metal batteries, graphite in the anode is replaced by a fine lithium-metal. This type of battery enables it to store double the power and withstand more than 6000 charging cycles compared to the current battery (Qian et al., 2015).

c. Metal-air: This battery relies on the reaction between oxygen and metal like lithium-air, aluminum-air, and sodium-air. Lithium-air is firstly proposed in the 1970s and has received more attention after recent improvements. The outstanding theoretical specific energy can reach 12 kWh/kg and the practical specific energy is 1.7 kWh/kg (Girishkumar et al., 2010). The advantages of aluminum-air batteries are higher energy densities of 6.2 kWh/L, and the recycling technology of related materials is more mature (Gelman et al., 2014; Mori, 2020). Sodium-air battery uses sodium, which is an abundant resource, as the cathode of the battery. The energy density of sodium-air reaches 4.5 kWh/L (Adelhelm et al., 2015).

d. Graphene: Offering high thermal conductivity and an ultra-light design, graphene-based options are seen as one of the potential EV batteries of the future. They enable fast or ultra-fast charging without significant power loss. While this type of battery is still at the early stage of development, an existing prototype can reach 1 kWh/kg (H. Kim et al., 2015).

e. Semi-solid lithium: Due to the inherently poor utilization of active material in traditional lithium batteries, a new electrode design is proposed (Deruta et al., 2011). A new method called semi-solid flow cell (SSFC) accounts for 10 times the charge storage density of the conventional flow-battery solution.

Such new technologies can increase the autonomy of EVs as well as reduce the charging time and range anxiety, further attracting new customers and heightening the popularity of EVs. However, these technologies still lack comprehensive validation and approval for commercialization. Furthermore, the maintenance strategy for these innovative batteries requires more investigation. Although the distinct chemical properties and performances of these proposed kinds of batteries may enhance the function of the EV, it is unknown whether the existing PHM technologies are applicable or if entirely new methods will need to be developed.

4.2. Charging Optimization

The charging process is a crucial factor for customers selecting EVs. The existing connector type is not universal due to the different charging standards and markets as we discussed in the previous sections. Even though adapters can be used, inconvenience, cost, and safety issues are expected. Also, due to the limitation of wired charging in the application area, wireless power transfer (WPT) has gained more attention in recent years (Bi et al., 2016; Panchal et al., 2018). WPT is mainly divided into two categories: capacitive power transfer (CPT) and inductive power transfer (IPT). Noteworthily, IPT is the most common application since it is suitable for different gap distances and charging standards while CPT is only applicable for relatively small gap distances. These wireless methods provide more flexible options for charging. However, they also present new issues like electromagnetic safety or magnetic field emission due to misalignment. The combination of WPT and existing charging technology to optimize the charging process as well as prevent reducing battery capacity from fast charging would be a key research topic in the future.

4.3. Infrastructure Evolution

Communication between EVs and charging infrastructures is also important. Currently, the number of charging points is still scarce in comparison to the traditional gas station (*How Much Charging Infrastructure Do Electric Vehicles Need?*, n.d.), which makes customers hesitant to buy EVs. Taking the charging price and charging demand into consideration, artificial intelligence algorithms can be applied to optimize the deployment location of the charging point and set up a dynamic charge price based on the loading of the power grid and period (Vazifeh et al., 2019; Zhang et al., 2015). The utilization of WPT makes real-time communication with charging infrastructure possible. The conventional wireless network and bidirectional WPT (BD-WPT) (Tang et al., 2018) can help users form the network between vehicles and power grids (V2G), finally leading to a complete vehicle-to-everything (V2X) service. The data from the vehicle and node on the power grid allows the realization of AI-based algorithms to be used to determine the optimization route of charging points that consider the autonomy of vehicles, price, power demand, charging facility, and completion time.

4.4. Sustainability

EV has been viewed as the representation of sustainable and eco-friendly transportation because of the zero-emission of greenhouse gas during the operation. However, the idea of sustainability of EVs is still questionable if we consider the manufacturing process, usage during the lifetime, and the waste after usage (Beaudet et al., 2020; Romare & Dahllöf, n.d.). Considering the manufacturing process, twice the energy can be required to produce an EV compared to a traditional vehicle, especially during the battery fabrication process (Romare & Dahllöf, n.d.). While EVs do not emit greenhouse gas during operation, the required electricity needed to operate the vehicle mostly comes from traditional fossil-fuel power plants which reduce the expected benefit to the environment. Therefore, off-grid charging from a renewable power plant or power storage station might be an alternative strategy (Falk et al., 2020). Finally, regarding the end life of used batteries, the increasing amount of EV battery waste will become a hazard to the environment without appropriate treatment (Beaudet et al., 2020; Harper et al., 2019). To address this recycling issue, three main methods of pyrometallurgy, hydrometallurgy, and direct recycling respectively are summarized in Figure **7**.

Pyrometallurgy is a high-temperature method to reduce the component metal oxides to an alloy of Co, Cu, Fe, and Ni, leading to the production of alloy fraction, slag, and gases while hydrometallurgy uses aqueous solutions to extract the desired metals. Direct recycling can remove the cathode or anode from the electrode to recondition and re-use the battery. Apart from the recycling method of battery waste, PHM technology can also help improve the sustainability of the battery. With the accurate estimation of SoC and SoH in the battery, the user can prevent the full discharge, further extending the battery lifecycle and allowing appropriate actions like battery maintenance scheduling or component replacement to occur.

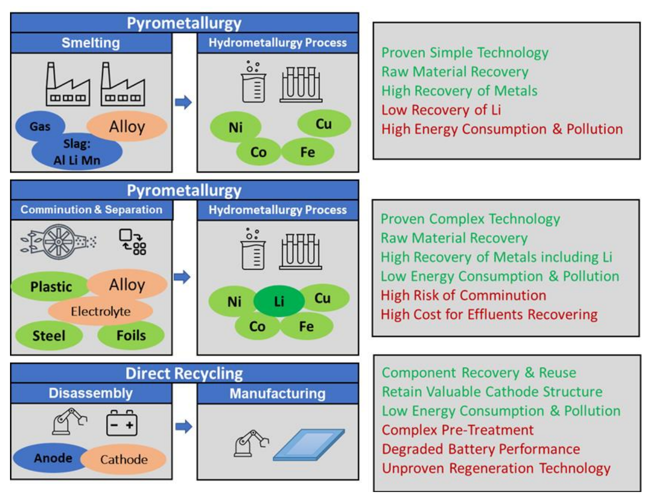

Figure 7. Main recycling methods of used battery

5. CONCLUSION

The various aspects of critical components found in the EV charging network and the challenges and opportunities in these networks are discussed in this paper. The overview of the charging network is illustrated to describe the energy flow from the power plant to the end-user and to explain the suitable application based on the different charging standards.

This paper briefly reviews the existing challenges from critical components such as the motor and battery to the whole service network. The corresponding proposed solutions and opportunities are also investigated:

At the component level:

Motor:

- Combination of robust feature extraction methods during idle or startup conditions and the PHM techniques

Battery:

- Combination of NDT methods and machine learning techniques to improve the accuracy of the battery model (applicable for different kinds of EV batteries)
- Research of SoC and SoH models based on public datasets with practical driving patterns and informative environmental conditions

Charging system:

- Accurate PHM model of the charging system during operation

At the system level:

- Cybersecurity and operation safety of charging network
- Research of optimization of high-impact elements on the whole charging network

From these surveys, four aspects of the future vision in EV charging networks are proposed based on the intelligent maintenance perspective:

Battery innovation:

- The comprehensive PHM research of new EV batteries

Charging optimization:

- Optimization strategy in the charging process with WPT and existing technologies

Infrastructure evolution:

- Realization of bidirectional communication between EVs and charging network

Sustainability:

- Combination of existing PHM technology and innovative battery waste recycling mechanisms for battery maintenance scheduling or component replacement

Thus, it is concluded that these suggestions could contribute to the innovation and development of EV networks and accelerate the deployment of EVs throughout the world.

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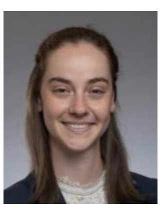

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