Electric Vehicles Charging/Discharging and Battery Degradation

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The high penetration of electric vehicles (EVs) will burden the existing power delivery infrastructure if their charging and discharging are not adequately coordinated. The degradation of lithium-ion batteries occurs throughout their lives due to several chemicals and mechanical processes that reduce the cyclable lithium and other active materials. Battery degradation depends on many factors, such as the charging and discharging rates, depth of discharge (DOD), temperature, voltage, cycle number, and storage stage of charge.

dynamic pricing electric vehicles neural networks

1. EV Charging and Discharging Techniques

There are four charging/discharging techniques, namely, uncontrolled charging-discharging [1][2], controlled charging-discharging [1][3], smart charging [1], and indirectly controlled charging [1]. **Table 1** summarizes the benefits and challenges faced by each charging/discharging technique. In addition, the schema of each charging technique is illustrated in **Figure 1**. The uncontrolled charging-discharging approach allows electric vehicles (EVs) to charge or discharge at rated power as soon as it is plugged in until the battery's storage level equals the maximum state of charge or unplugged [1][2]. Thus, this charging method is inflexible for demand-side management DSM (Demand-Side Management) [1]. The uncontrolled charging technique is convenient for EV owners to make charging decisions freely. However, uncontrolled EV charging might cause a negative impact on local distribution networks, such as power loss, demand-supply unbalance, shorter transformer lifespan, and harmonic distortion [4].

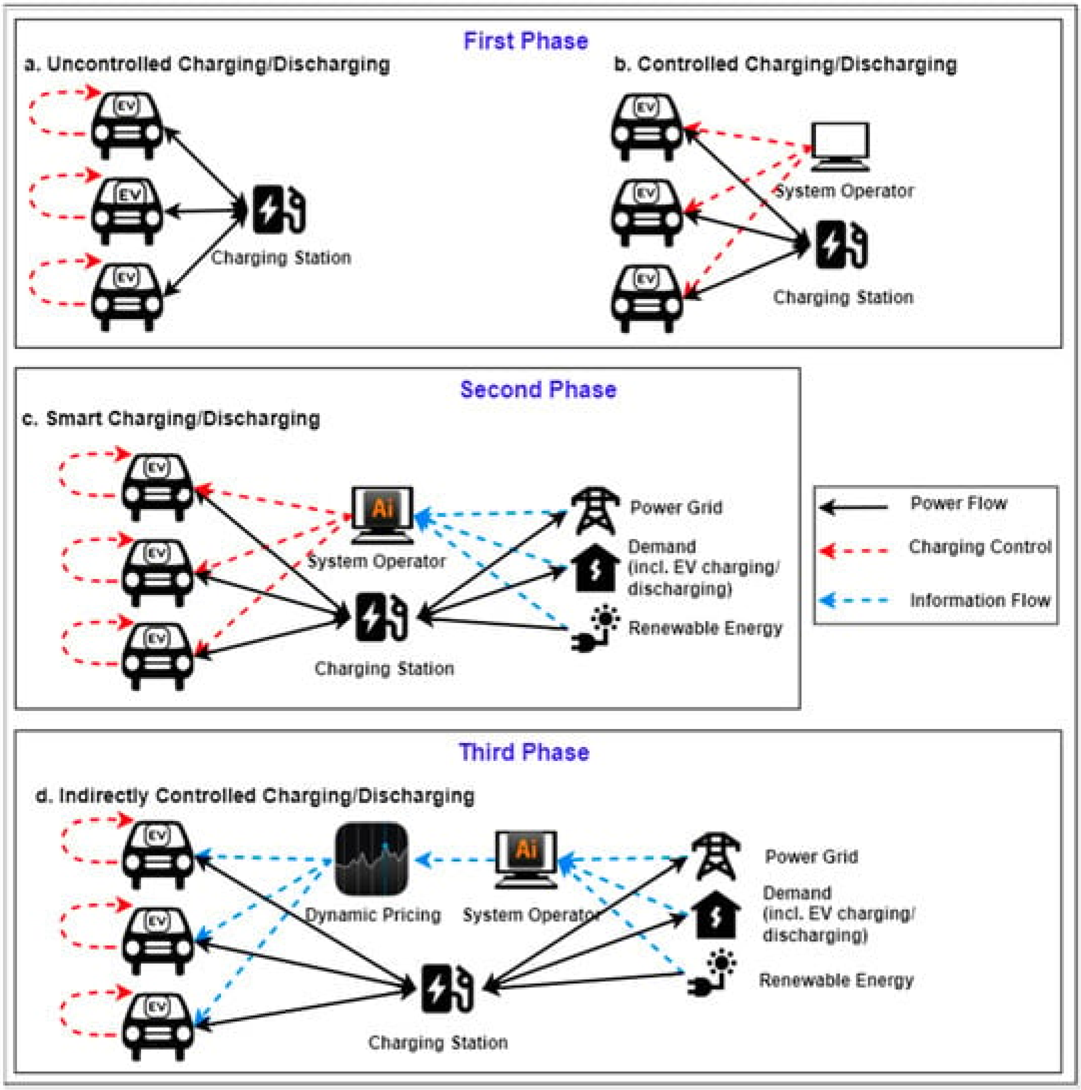

Figure 1. Schema of vehicle-to-grid (V2G) development phases and corresponding EV charging techniques, (**a**). smart charging, (**b**). controlled charging, (**c**). smart charging, (**d**). indirectly controlled charging. The solid black arrow indicates the power flow, the dash red arrow indicates the charging control, and the blue dash arrow indicates the information flow.

Table 1. Summary of different EV charging and discharging techniques.

Techniques	Benefits	Challenges
Uncontrolled	• Easy implementation • EV owners have the freedom to make charging decisions • Convenience for EV owners	• Add burden to power grids • Charging costs might be higher than smart charging • Inflexible for demand-side management

Techniques	Benefits	Challenges
Controlled	• System operators have more freedom to make decisions	• EV owners have to cede control to the system operators
Smart	• Balance demand and supply • Make charging decisions based on the real-time conditions • Maximize profits for power system operators	• Hard to encourage EV owners to participate in smart charging • Benefits for EV owners are usually unclear
Indirectly controlled	• Use monetary terms to encourage EV owners to participate in smart charging • Incentive is clear	• Electricity pricing signals need to be accurate to be effective

The controlled charging-discharging method, also known as unidirectional V2G, gives system operators more freedom to decide when EVs will be charged and discharged [1][3]. However, EV owners have to cede control to the system operators or aggregators immediately after the EV is plugged in under the controlled charging-discharging strategy [5].

The smart charging technique manages EVs' charging and discharging based on real-time energy demand, grid requirements, and grid quality [1]. However, it is not easy to encourage EV owners with different preferences to participate in smart charging programs without incentives [6]. Smart charging allows EV owners to charge or discharge their EVs at a certain time and rate to achieve predefined goals such as minimizing charging costs or balancing demand and supply. However, smart charging strategies are usually designed by system operators to maximize their profit. In addition, EV owners do not clearly understand how smart charging can benefit them monetarily.

On the other hand, an indirectly controlled charging mechanism uses more straightforward price signals to incentivize EV owners to provide ancillary services to power grids. Wang and Wang [7] suggested using macro-incentive policies such as variable electricity tariffs to attract more EV owners to participate in the V2G system [7]. Dynamic pricing schemes [8], such as Time of Use (ToU) and Real-Time Pricing (RTP), have been commonly used as a special form of power load demand response, which encourages EV owners to choose charging or discharging time according to financial incentives [1][9][10][11]. Dutschke and Paetz [12] conducted two empirical studies in Germany to get the public's opinions about the dynamic electricity pricing determined by the Time of Use (ToU) tariff and household load profile. The results indicate that consumers are open to dynamic pricing but like more straightforward programs with a smaller price fluctuation range [12][13]. Latinopoulos et al. [14] investigated EV drivers' responses to the dynamic pricing of parking and charging services. The results suggest that younger individuals are more likely to exhibit forward-looking behaviors. Therefore, indirectly controlled charging with dynamic electricity pricing strategies will influence EV owners' charging and discharging behaviors.

2. Vehicle to Grid (V2G) Concept

The V2G technology allows EVs to utilize onboard batteries as an energy source for driving and energy storage systems for power grids [15]. Therefore, utilizing EVs' batteries with fast charging and discharging reaction time (as fast as tens of milliseconds [3]) as energy storage and power sources via V2G technology can avoid additional investment for a battery storage system. In addition, average cars are parked 95% of the time, equivalent to the total operating hours of baseload generators [15]. Therefore, V2G technology can benefit system operators by providing ancillary services and energy storage for renewable energy. It can also reduce EV owners' charging costs by allowing them to sell extra stored energy back to power grids. Parsons et al. [16] investigated potential EV owners' willingness to pay for an EV with V2G capability and contract terms. The survey results suggest that the V2G concept is most likely to attract more EV buyers if power aggregators provide either upfront cash payment or pay-as-you-go basis types of contracts.

Lund and Kempton [17] modeled a power system that integrates renewable energy into the transport and electricity sectors using V2G technology. The simulation results indicate that adding EVs with V2G capability can enhance renewable energy utilization (i.e., align EV charging pattern with renewable energy generation pattern) and reduce CO_2 emissions. Scott et al. [1] simulated a V2G model for a university campus under various charging scenarios. The simulation results show that using EVs' batteries as energy storage over ten years can reduce electricity costs by 64.7% and 9.79%, respectively, compared to purchasing electricity from the power grid and using sole battery storage [1]. Al-Awami and Sortomme [18] have formulated a mixed-integer stochastic linear programming model to coordinate V2G services with energy trading. The simulation results show that using V2G services to coordinate short-term energy trading can increase the profit of the load-serving entity (LSE) by 2.4% and reduce emissions by 5.3% compared to the uncoordinated one. The advantages and disadvantages of the V2G concept are summarized in **Table 2**.

Table 2. Summary of the advantages and disadvantages of V2G.

Advantages	Disadvantages
• Avoid additional investment in a battery storage system • Enhance renewable energy utilization, thus reducing emissions • Mobile energy storage with a fast reaction time	• Battery degradation concerns • Charging-discharging efficiency concerns • Additional upfront investment

Advantages	Disadvantages
• Provide ancillary service for power grids	
• Reduce charging costs for EV owners	

Although V2G technology can potentially provide many benefits to power systems and EV owners, the implementation of V2G still faces some challenges, such as high upfront investment [19], battery degradation [15], and charging-discharging efficiency concern [20]. In addition, the V2G concept is still relatively new and evolving. Many pilot V2G projects remain in the development stages [21]. By 2018, only 2 out of 486 (0.41%) utilities investigated by the Smart Electric Power Alliance (SEPA) had implemented the V2G pilot project [22]. By 2022, there were only around 100 V2G plot projects with different scales and testing phases worldwide [23][24]. Therefore, to accelerate V2G implementation, the charging and discharging efficiency need to be improved. On top of that, the V2G payment procedure and contract terms need to be simplified. Batteries' degradation rate and upfront investment of V2G need to be quantified to allow EV owners to make informative decisions.

3. Battery Degradation and Charging Efficiency

The degradation of lithium-ion batteries occurs throughout their lives due to several chemicals and mechanical processes that reduce the cyclable lithium and other active materials [25]. Battery degradation depends on many factors, such as the charging and discharging rates, depth of discharge (DOD), temperature, voltage, cycle number, and storage stage of charge, which are complex to quantify [7][19][25]. The degradation of the battery can be classified into two types: calendar aging and cycle aging. Calendar aging occurs during storage, whereas cycle aging happens during charging and discharging. Battery temperature and state of charge (SOC) are the key factors that influence calendar aging, whereas cycle aging is affected by cycle number, charging rate, and DOD [26]. Therefore, additional cycle numbers due to the V2G service will accelerate battery degradation. It is important to quantify the degradation due to V2G service. Thus, adequate battery monitoring systems are needed to monitor the batteries' SOC and state of health (SOH) during the charging and discharging process. Meng et al. [27] performed a Lithium-Ion battery monitoring and observability analysis with an extended equivalent circuit model. As a result, the necessary observability conditions for battery capacity are clearly indicated, which can be used to aid battery charging control design. Meng et al. [28] proposed a Kalman filter and Gaussian process regression-based battery end-of-life (EOL) prediction model. The simulation results show that the proposed model provides a better battery EOL prediction than the particle filter, a popular method for battery EOL prediction. The effectiveness of Gaussian process regression on battery SOH estimation is also shown in [29]. Chaoui and Ibe-Ekeocha [30] proposed a recurrent neural networks(RNNs)-based SOC and SOH estimation model which does not require battery modeling or knowledge of batter parameters. The simulation results indicate that the recurrent neural networks-based estimation model can make good SOC and SOH estimations based on measured voltage, current, and ambient temperature. The measured data's accuracy is vital for empirical models' performance.

More charging/discharging cycles occur in the V2G service than when there is no V2G service; thus, battery degradation due to V2G services might be more severe than without it [26]. Petit et al. [31] assessed the impact of V2G on two types of Lithium-ion batteries, nickel cobalt aluminium oxides (NCA) and lithium ferro-phosphate (LFP). The simulation results indicate that the effects of V2G on different batteries are different. For example, NCA is more sensitive to cycle aging compared to LEP cells. In addition, high SOC can increase battery capacity loss during storage. Pelletier et al. [32] also indicated that the calendar aging process occurs faster for the battery stored at high SOC. The authors in [32][33][34] found that battery overcharging and over-discharging degradation happen when the battery operates outside its specified voltage range. Although battery degradation is inevitable at the moment, it is possible to minimize the process by avoiding overcharging/over-discharging and encouraging charging/discharging batteries at an optimal rate, under the optimal temperature range, and storing the battery at an optimal SOC. Therefore, battery degradation estimation and modeling need to be more accurate to support battery charging and discharging control design.

Besides battery degradation concerns, charging and discharging efficiency is also one of the primary concerns of the V2G program. Apostolaki-Iosifidou et al. [20] conducted experimental measurements to determine power loss during EV charging and discharging. The measurement results indicate that most power losses occur in the power electronics used for AC-DC (Alternating Current-Direct Current) conversion [20]. Usually, the highest efficiency of the power electronics occurs at the top region of their rated power [20]. In addition, the efficiency of the power electronics is higher during charging than discharging [20]. This is due to the higher voltage during charging than discharging at a given power. The higher charging voltage results in a lower charging current, thus lowering internal resistance losses [35]. Therefore, the trade-off between inevitable battery degradation and power loss during battery discharging and the benefit of V2G needs to be farther investigated. More research on battery design and management is required to minimize battery degradation during charging/discharging.

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