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Review

The role of artificial intelligence in the mass adoption of electric vehicles

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SUMMARY

The electrification of mass transportation is hailed as a solution for reducing global greenhouse-gas emissions and dependence on unsustainable energy sources. The annual sales of electric vehicles (EVs) has continued to rise since 2011, with a global sale of EVs of 2.1 million in 2019. This increase in sales is mainly due to continued improvement in the cost and performance of commercial EVs, increased EV options available to consumers, and environmental awareness. However, despite the positive outlook, EVs still face major challenges that hinder their rapid and widespread adoption: limited driving range, long charging times, and a lack of sufficient charging infrastructure. This review outlines the recent advances in EVs and related infrastructure, mainly from artificial intelligence (AI), which makes EVs a more attractive consumer option. The application of AI in improving EVs, facilitating EV charging stations, and EV integration with the smart grid is critically analyzed and reviewed. Finally, future trends and prospects in the area are discussed.

INTRODUCTION

Currently, global energy generation and transportation rely heavily on unsustainable and nonrenewable fossil fuels, namely coal, oil, and gas. Apart from the limited supply of these fossil fuels, they also pose serious climate problems, geopolitical tensions, and health risks.[1,2] In response to the detrimental effects of fossil fuels for energy generation and transportation, governments have proposed initiatives, such as the Paris Agreement, to curtail its use.[3] The transition to renewable and cleaner energy sources, such as solar, wind, and geothermal, for energy generation and the electrification of transportation has been deemed an effective solution to our reliance on fossil fuels and associated emission problems.[4] The last decade saw a rise in the sales of electric vehicles (EVs), with global sales of 2.1 million EVs in 2019.[5,6] There has also been a rise in electric automotive manufacturers, which has given a wider range of EV options for consumers. Although Nissan and General Motors were among the few US manufacturers in 2012, major existing and new manufacturers, including BMW, Chevrolet, Tesla, Volkswagen, Renault, Honda, Skoda, and Opel have joined the race for EV sales in 2020. Growing consumer interest in EVs can be attributed largely to the advent of new charging infrastructure, awareness of EV environmental benefits, increase in EV performance and design specifications, and the cost reduction of EV battery packs.[7,8] However, despite the positive outlook of EV integration in society, EVs still face challenges to their widespread adoption. These challenges include EVs' limited range and the associated user range anxiety, lack of charging infrastructure, the high upfront cost of EVs compared with that of traditional internal combustion engine vehicles, and safety concerns.[9,10] Therefore, developing related novel techniques and proposing useful strategies are necessary to overcome those challenges.

Context & scale

Current global energy production relies heavily on unsustainable fossil fuels (coal, oil, and gas), and the use of these fuels poses serious problems: climate change, an increase in geopolitical tensions, depletion of these limited resources, and adverse health effects. As a result, major global environmental groups and governments have setup initiatives and plans to reduce carbon emissions and combat climate change, for example, the Paris Agreement. Renewable power generation and the electrification of transportation have seen massive research and commercial developments over the last decade. Despite the numerous environmental and performance advantages of current commercially available electric vehicles, electric vehicles still have a small market share in the automotive industry. Compared with conventional internal combustion vehicles, this lack of consumer interest in electric vehicles (EVs) lies mainly in higher upfront costs, limited driving range, and lack of facilitating infrastructure.

Regarding high upfront costs, it is essential to bring the battery pack's cost down in the EV. Machine learning provides a cost- and time-effective approach to discover low-cost and high-performing battery materials and

Recently, artificial intelligence (AI), which is defined as algorithms supporting models aimed at mimicking natural thinking, perception, and action,[11] has seen industrial and academic applications in the field of EVs and related infrastructures, such as in EV battery design and management, charging stations, and even the smart grid.[11–14] Within this review's context, AI algorithms encompassing fields of machine learning and computational intelligence are considered. Depending on the problem, these AI algorithms can outperform classical rule-based systems (also called expert systems), which uses human knowledge to define rules within a system, due to their ability to find unusual trends and simpler implementation.[15,16] Several attractive advantages of AI application include: (1) EV cost reduction through optimal battery-material design and manufacturing,[17,18] (2) accurate range estimation to mitigate EV consumer range anxiety by predicting future driving conditions,[19] (3) improved EV energy consumption versus traditional controls using AI controls for the EV auxiliary systems,[20] (4) a potential for increased road safety and optimal traffic flowthrough connected and autonomous driving,[13,21] and (5) a thorough and efficient modeling approach for optimal location and resource allocation for electric vehicle charging stations (EVCSs) and energy scheduling for EV interaction with the smart grid.[22]

For a better understanding of this topic, the AI techniques mainly used in EVs and related infrastructures are summarized and divided into machine learning (ML) and computational intelligence (CI), as shown in Figure 1. To be specific, ML models are adept at finding relations and trends between inputs and outputs based on previous observations, and they require training on a previous dataset. The ML used in EVs and related infrastructures can be roughly classified into supervised, unsupervised, and reinforcement learning (RL). The supervised and unsupervised learning have been researched and applied in areas within EV and its infrastructure where large datasets are available or can be created, such as in EV battery-state estimation and discovery of new materials for the EV batteries.[23,24] Their basic concepts are displayed in Figures 1A–1C, in which the deep-learning (DL) model uses architectures involving neural networks (NN) with more than one hidden layer[25]; RL aims to learn the best course of action on its own through trial and error, and the agent interacts with its environment through actions and is rewarded accordingly.[26]

Aside from ML, CI algorithms (as shown in Figures 1D and 1E, are commonly used for solving search, optimization, and other complex problems.[27] Within the EV context, CI algorithms are instrumental in solving complex, dynamic optimization problems, such as the optimization of control systems within EV, optimal placement of EVCSs, and integration of EV infrastructure with the smart grid.[28–30] Although the current EV market has not yet fully embraced AI, the number of related academic publications, patent applications, and the production scale have increased rapidly in the past decade. An overview specifically for the roles of AI in EVs and their infrastructure is rare but is important to accelerate the progress of R&D and mass industrial application and commercialization.

This review focuses on those areas within EV and its infrastructure where AI can impact EV's mass adoption. The outline of this review is illustrated in Figure 2; aside from the basic introduction above, the use of ML and CI in battery manufacturing and management within EV and EV auxiliary control systems are discussed first. Furthermore, the role of AI in the optimal location selection and resource allocation of an EVCS, and seamless integration of EV and the smart grid are considered in the subsequent two sections. Finally, future research orientations are also provided to address challenges such as high-throughput data generation, performing *in situ* calculations, and the scalability of data from battery-level to battery-pack scale, for further research, technology applications, and commercialization.

increase battery-manufacturing efficiency. Artificial intelligence (AI) algorithms and controllers can provide a realistic driving-range estimation and optimize energy conservation, which can add extra driving range and reduce consumer "range anxiety." Access to charging stations and the smart grid can significantly improve the consumer appeal of electric vehicles. Vehicle-to-grid (V2G) technology in the smart grid provides EV owners with an opportunity to earn revenue by providing power to the grid. AI algorithms make it easier to manage EVs and power-generation interactions by estimating optimal locations and resources for charging stations, reducing congestion in charging stations, and managing energy distribution in V2G technology.

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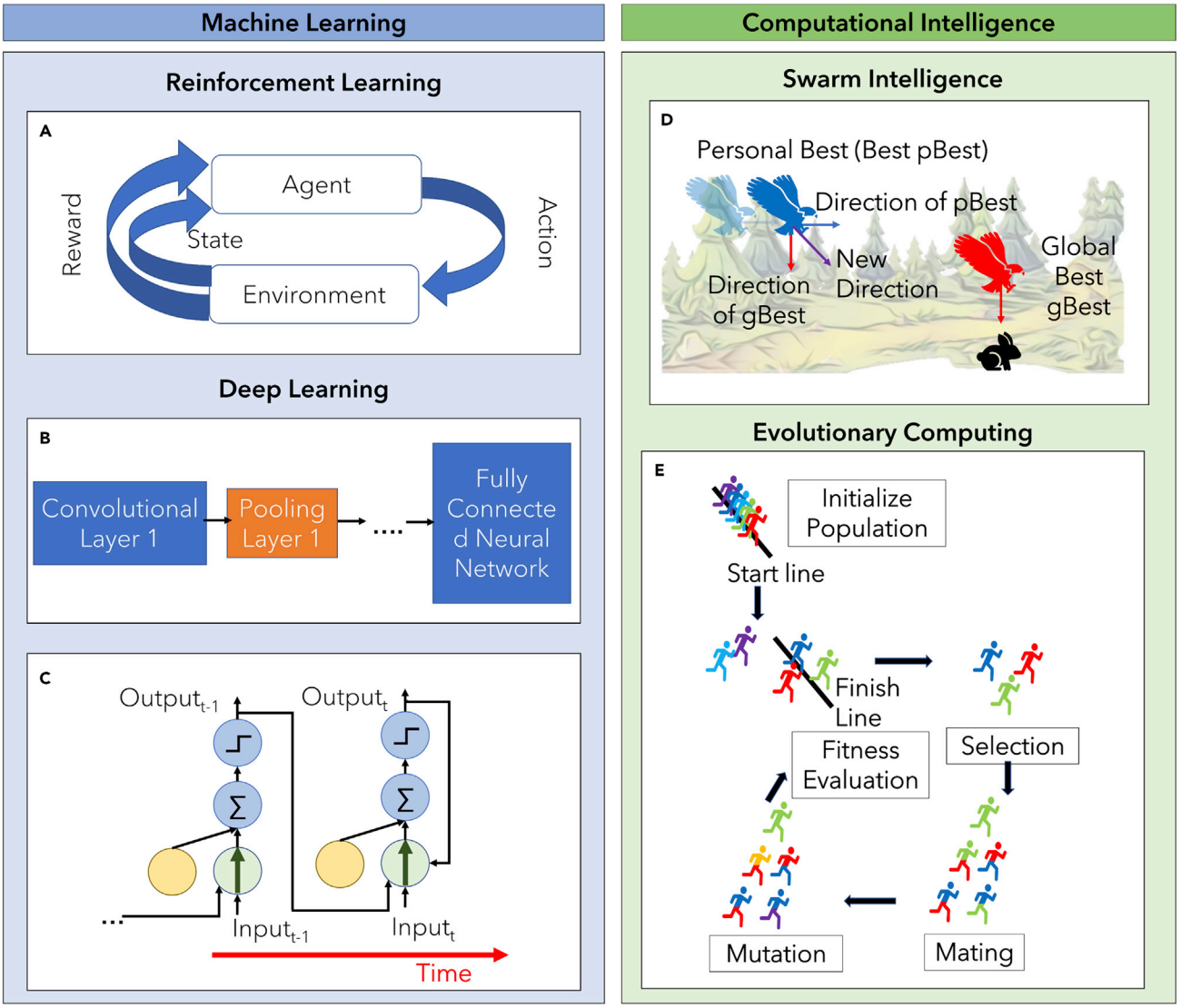

Figure 1. AI techniques (ML and CI) used in EV and mass adoption

(A) Process flow for reinforcement learning. The agent interacts with the environment and gains a reward accordingly based on its action. Through iterative learning, the agent learns and adopts a policy that aims to maximize its reward.

(B) Commonly used architecture for convolution neural networks (CNN). CNN, commonly used for image processing, as successive layers of convolutional and pooling layers are connected to a fully connected neural network. Convolutional layers filter the image based on high-level image features while the pooling layer compresses the image to reduce its size for ease of handling.

(C) Neural network of recurrent neural networks (RNN). RNN, commonly used for time series analysis, has the output of the neural network at (t-1) time-step as the input of the at t time-step. The image shows a single RNN unrolled in time.

(D) Depiction of the process flow of particle swarm intelligence (PSO). PSO, commonly used for search and optimization engineering problems, has a swarm of particles, which search in the solution space. The particles communicate both a particle's personal best and the global best to find the solution.

(E) Depiction of the process flow of genetic algorithm (GA). GA, commonly used for search and optimization engineering problems, has an initial population of solutions. During each iterative process, the population undergoes mutation and crossover operations to find the solution.

AI IN ELECTRIC VEHICLES

The safety, reliability, and economic feasibility of EVs are critical for their mass adoption, and those properties can be significantly improved through the implementation of AI. Applications of AI in EVs have been widely investigated and can be roughly divided into several categories, including EV battery design, manufacture,

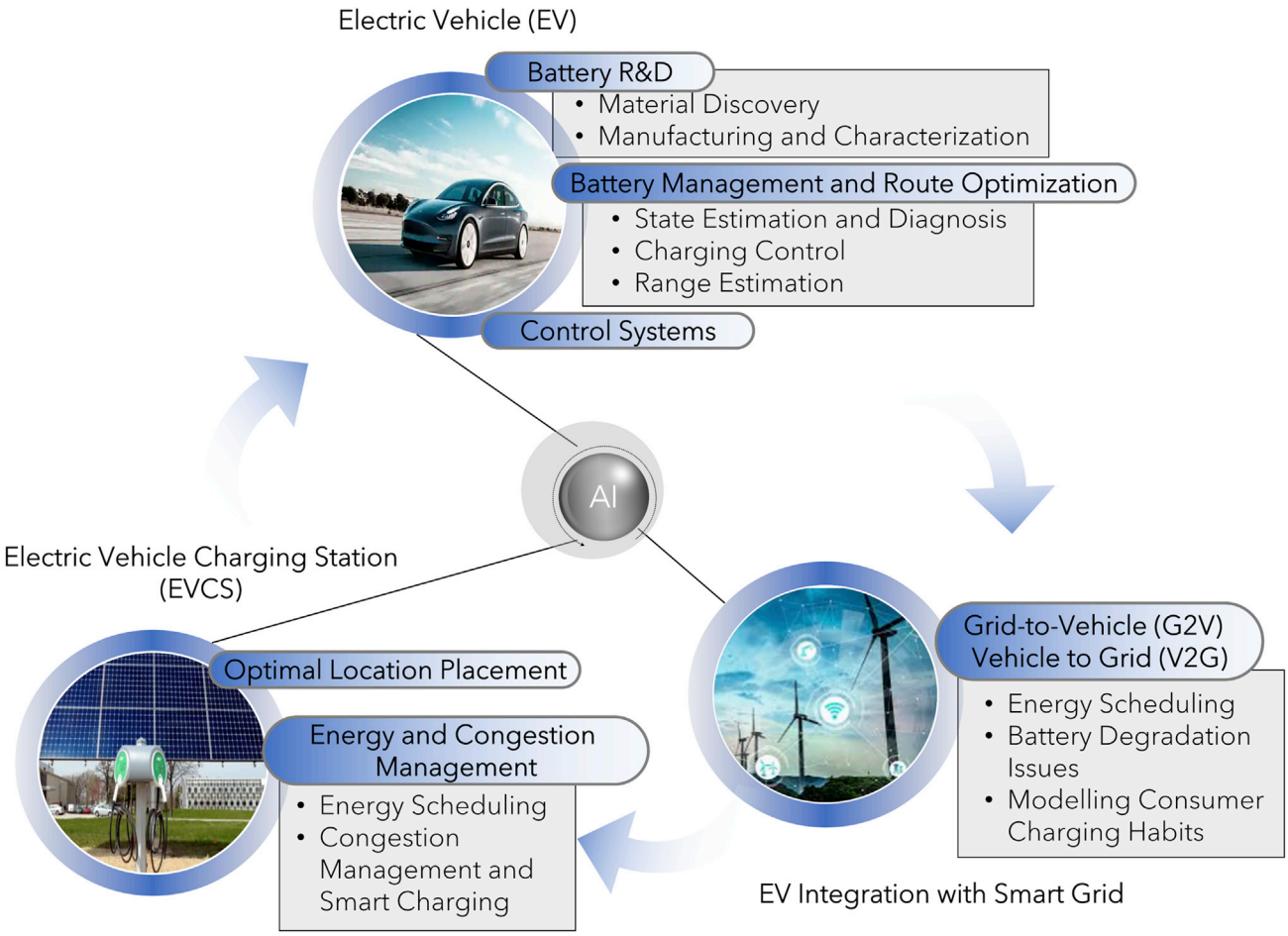

Figure 2. Overview of the use of AI in EV, EVCS, and EV integration with smart grid

This review covers the some of the application areas of AI for EVs, EVCSs, and the integration of EV with smart-grid systems. Within EV, AI has been utilized for battery R&D to improve battery performance, battery-pack management, and energy management. For EVCSs, the use of AI for optimal EVCS placement, congestion control, and reliable energy scheduling are discussed. Finally, the efficient energy management during the two-way energy transfer between EV and the smart grid, enabled by grid-to-vehicle (G2V) and vehicle-to-grid (V2G), using AI techniques, are reviewed.

and management; range optimization; as well as EV control-system design and optimization.[24,31] In this article, the energy-related content, i.e., the use of AI technologies in battery management and range optimization for energy efficiency enhancement, will also be a focus.

ML in battery R&D

As core components, batteries, especially the lithium batteries, play an important role in providing the power source and energy storage for EVs. In an EV battery pack, individual batteries are connected and assembled into battery modules, which in turn are connected and assembled into a battery pack. The combination of series and parallel connections of the batteries within a module and the modules within a battery pack provide the desired potential and capacity.[32] However, current EV batteries still face performance-related issues resulting from barriers in battery design and manufacturing to the battery management and optimization during operation in EVs. Limitations in battery design and manufacturing lead to lower energy-density of the EV battery pack, resulting in increased cost.[33] Additionally, more energy-efficient EV batteries can drastically alleviate user range anxiety. To achieve higher

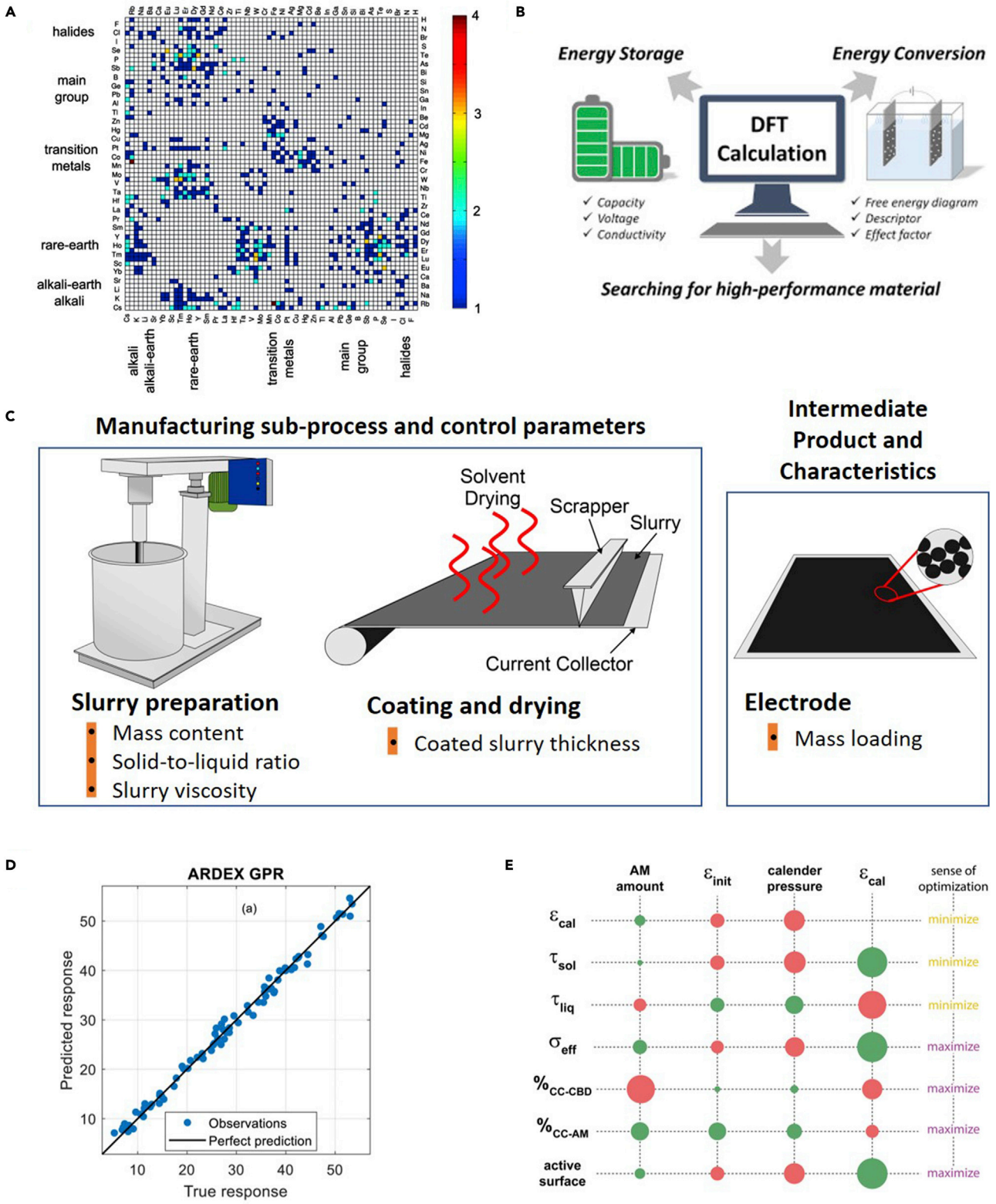
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Figure 3. ML models for battery-material discovery and manufacturing-efficiency improvement

(A) Heatmap illustrating the available chemical heatmap and suitable potential materials discovered by ML techniques. Reprinted with permission from Hautier et al.[46] Copyright 2010 American Chemical Society.

(B) Discrete Fourier transformation (DFT) calculations for energy storage and conversion. These calculations can be used to find relevant electronic properties of the materials for ML training and testing dataset training. Reprinted with permission from Wu et al.[47] Copyright 2019 Elsevier BV.

(C) An example of a battery-manufacturing process including slurry preparation and coating the slurry onto the current collector. Furthermore, the examples of process controls of these subprocesses are shown that can be optimized and affects the intermediate product's (battery electrode in this case) characteristics (mass loading in this case).

(D) The ML-based regression model evaluation, which shows high accuracy in predicting the electrode mass loading (intermediate battery characteristic) from the manufacturing process controls Reprinted with permission from Liu et al.[48] Copyright 2021 Elsevier.

(E) The interdependence of the intermediate product characteristics with the manufacturing process control from studying the ML models. Reprinted with permission from Duquesnoy et al.[49] Copyright 2020 Elsevier.

energy efficiency, consumer perception, safety, and economic feasibility, ML techniques to overcome the above challenges have received increased academic and commercial attention. By facilitating battery-material discovery, characterizations, and improving battery-manufacturing efficiency, ML can lead the way to higher battery energy efficiency and safety and improve consumer perception of EV range.

Coupled with advances in quantum mechanics (QM) and computational advancements and the availability of materials datasets, ML provides a less capital- and time-intensive approach for battery material discovery and characterizations than traditional approaches.[17,31,34] ML techniques effectively explore the chemical space for new material discovery (Figure 3A) of higher energy density and safer battery electrodes,[35–38] solid electrolytes,[39,40] and electrolyte addictives.[41] Also, ML techniques can account for complex molecular interactions, reaction pathways, and minimization of side reactions.[42] The dataset for the chemical and quantum mechanical properties of known chemical species is crucial for new material discovery. Examples of publicly available and comprehensive datasets include Materials Project,[43] the Chemical Space P roject,[44] and QM9.[42] ML techniques are frequently employed to predict the anticipated properties of new materials from other known properties by exploiting the trends of the existing known materials in the database. QM calculations or databases (e.g., QM9) are used to estimate the chemical properties, which are hard to measure experimentally or unknown, of existing materials and these chemical properties are used as inputs to the ML techniques (Figure 3B). For example, QM calculations can estimate the redox potential and molecular band-gap information from molecular composition. A suitable ML technique can be trained by using this information along with other known relevant chemical properties, which can be used to estimate the redox potential of currently nonexistent molecules.[45]

To further facilitate material discovery, ML can also automate, thereby removing human biases in electrochemical and material characterization techniques, such as electrochemical impedance spectroscopy (EIS),[50–52] cycle-life testing,[50,51,53,54] and tomography.[55] Although numerous research work has been demonstrated, ML-based approaches to battery design have lacked commercial interest because of numerous reasons, namely, insufficient dataset size,[24] and the reluctance of the mature Li-ion battery industry to change battery materials.[56,57] Materials datasets used in research work can be quite small, especially when hard-to-quantify material properties are used.[24] Small datasets affect data quality negatively and limit the ML's model selection and accuracy. Moreover, shortages of government funding in material science, long time frames for commercially viable material developments, and a lack of relevantly skilled employees induces industrial hesitance to adopt new materials.[57,58]

Another strategy to improve battery energy density is to tweak the characteristics of the intermediate product (e.g., battery electrodes) during battery manufacturing

(Figures 3C and 3D), ensuring the battery's energy density is close to its maximal theoretical limits. For example, increased electrode surface area can lead to a higher discharge capacity of a battery.[59] Recently, some research works have used ML to predict the intermediate physical product characteristics from manufacturing process parameters.[18,37,48,60–62] These process parameters can be chemical compositions, such as during electrode active area fabrication or manufacturing equipment parameters (e.g., the spinning speed of mixers). For instance, Lui et al. utilized an ML regression-based model to predict the electrode mass loading from control parameters involved in slurry mixing (mass content, solid-to-liquid ratio, and slurry viscosity) and coating onto the substrate (comma gap) during electrode fabrication.[48] This research area is relatively recent and suffers from the lack of readily available relevant datasets. Researchers have to design and generate their datasets experimentally,[18,48,63] which is a time-, capital-, and labor-intensive process. The dataset from the work of Liu et al. is publicly available,[64] but has limited research usefulness because of a lack of input features. More datasets might be available in the future as the research and commercial work in this field increases. Simulations using physical and empirical models can be used for quick dataset generation.[60,49,65] For instance, Takagishi et al. trained an artificial neural network (ANN) by using simulation results from zero-dimensional electrochemical models, and this ANN can predict the charge-discharge specific resistance from the electrode porosity features (porosity, active material particle size and volume fraction, and compaction process pressure); electrolyte conductivity; and binder/additive volume fractions.[60] Although this approach can generate a large dataset in a cost- and labor-intensive fashion, it does not account for real-world phenomena, such as complex interdependencies between manufacturing processes, and depends on the reliability of simulation results.[49] Combining insights from experimental results into model-based simulations can ensure high simulation reliability while generating large datasets for ML algorithm training.[49] Moreover, more studies need to study the interdependence between the manufacturing process and the output using insights from ML (Figure 3E).

ML in battery management

In EVs, the battery-management system (BMS) is responsible for battery-pack sensing, battery-state estimation, and diagnosis and ensures energy-efficient control of the EV battery pack (Figure 4A).[66] BMS typically uses the voltage, current, and temperature of each battery module to compute state-of-charge (SOC) and state-of-health (SOH) for battery-state estimation and diagnosis, respectively.[67] Battery-pack SOC and SOH estimation are challenged by nonlinear battery characteristics within each cell and inconsistencies in performance between them.[14,67,68] The traditional SOC estimation method includes referencing from look-up tables, ampere-hour integral methods, and model-based estimation methods, including equivalent circuit models (ECMs) and electrochemical model (EMs). Similarly, SOH in EV has traditionally been estimated by using ECM or other empirical models. However, these methods for state estimation cannot predict the states accurately and/or computationally expensive. Whereas EM-based models typically provide higher SOC and SOH accuracy than ECM, EM calculations require high computational resources, which makes them unsuitable for real-time EV applications.[67] Here, the term "computational resource" refers to the resource used by some computational models in the solution of computational problems, such as memory space, amount of storage, computation time, etc. Accurate health and power estimation are critical for reliable and safe operation to prevent EV malfunctions and potentially serious accidents.[12,14,69] ML-based state estimation is considered a promising approach for EVs because of its lower computational demand, accuracy, and lack of need for extensive mathematical models (Figure 4B).[14,67,69] Moreover, a hybrid approach,

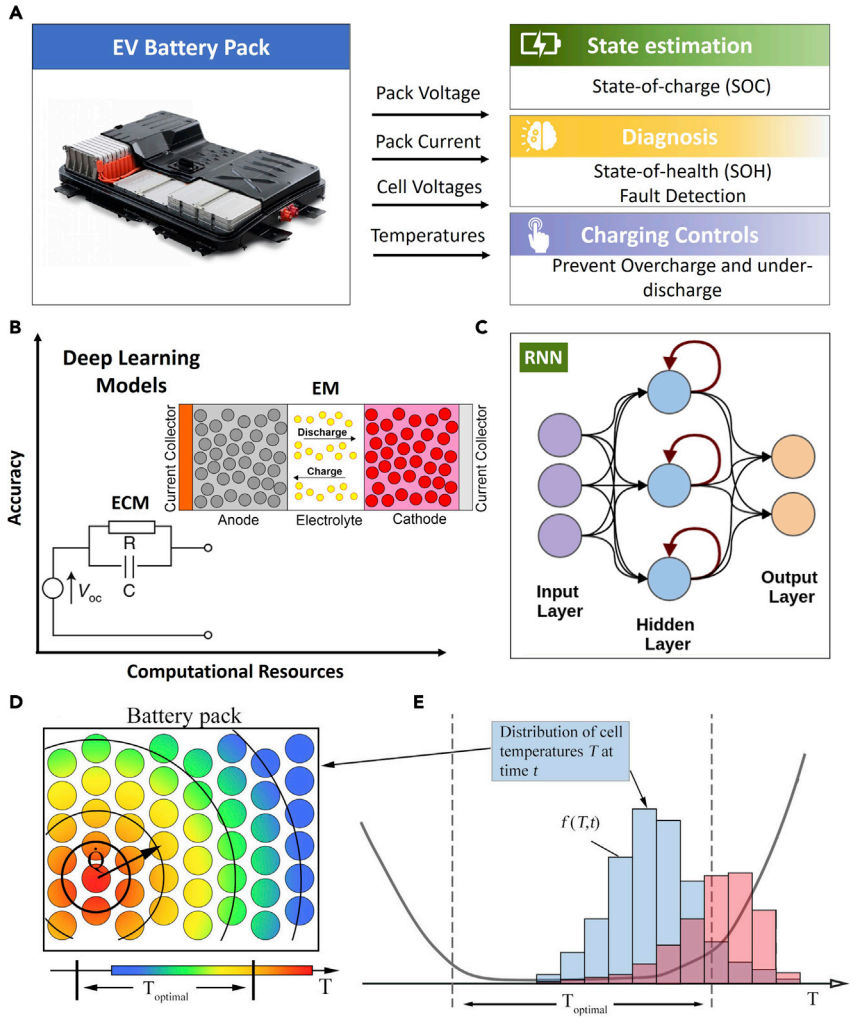


Figure 4. Machine learning (ML) in battery management

(A) The battery-pack sensor input information to the battery-management system. The battery-management system collects the time series data, consisting of pack voltage, pack current, voltages of individual cells, and temperatures from the temperature probes at intervals.

(B) Accuracy versus computational resources required for SOC and SOH estimation. When measuring SOC and SOH, data-driven models, powered by deep learning algorithms, show higher accuracy than the ECM models and much lower computational resources compared with physical models, such as single-particle models.

(C) Schematic diagram of recurrent neural networks (RNNs).

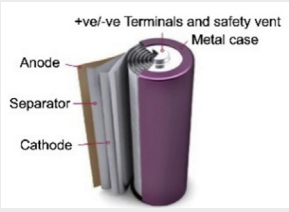
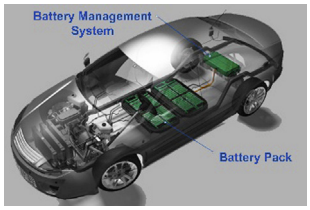
(D) The temperature profile of the battery cells in a battery pack. Adapted from Karlsen et al.[71] under the Creative Common License [https://creativecommons.org/licenses/by/4.0/].

(E) The temperature profile of the batteries can be visualized as a histogram.[71] The temperature variation can be trained by using an RNN to predict the future temperature values, which can be compared with actual values for anomalies.[72] Adapted from Karlsen et al.[71] under the Creative Common License [https://creativecommons.org/licenses/by/4.0/].

in which ML and ECM/EM models are combined, can be used with higher SOC and SOH prediction accuracy and low computational resource requirements.[70] An overview of ML-based estimation methods for SOC and SOH is presented below.

As noted above, pretrained ML models can model the nonlinear dependencies to state estimation without having high computational requirements as required by

Table 1. ML approaches at different cell levels

Level	Sub-Level	Aim	ML Input	ML Output
Cell 	cell material design	improve battery energy density, safety, and cost (<100 USD/kWh)	chemical property from experiments or DFT calculations	electrochemical property
	cell manufacturing	battery cost reduction (<100 USD /kWh)	process parameter	process quality
System 	battery-management system	SOC SOH fault detection	individual battery terminal voltage temperature	SOC SOH faulty battery, location, and time

DFT, density functional theory; SOC, state of charge; SOH, state of health.

EM. In the case of pretrained ML models, such as NN, the result usually requires simple matrix multiplication (the matrix containing weights and biases in the case of NN), whereas EM models require simultaneous numerical solution of nonlinear partial differential equations.[25,73] Publicly available battery dataset sources useful for SOC/SOH estimations include the NASA Acme dataset,[74] CALCE battery group,[74] and Severson et al..[53] Among other supervised ML algorithms, NN[75] and SVM[76] have been often used for SOC estimations. However, these algorithms have shown to have low accuracy rates (typically around 2%). For instance, a two-layered NN with a filter to remove noise shows an accuracy of just about 2%.[75] However, employing DL algorithms can significantly improve the SOC estimation accuracy.[76] This accuracy in SOC estimation comes from increasing the number of hidden layers, but overfitting the data can become a challenge. In particular, recurrent neural networks (RNN)-based models can be useful as it can consider the battery history and evaluate the battery's dynamic aging and hysteresis (Figure 4C).[77] Similarly, RNN has also been successfully employed to estimate SOH.[78] Types of RNN architecture, including RNN-gated recurrent units (RNN-GRU) and long short-term memory (LSTM), can effectively capture the long-term battery characteristics. The inputs for ML algorithms in SOC and SOH estimations are listed in Table 1. Hybrid models have shown SOC prediction, with an error of less than 1% in some cases,[70,79] while requiring much less computation resources than ECM/EM models.[69,70,79] However, for real-time EV applications, the computational power of the current BMS in EV needs to be considered. Further challenges to ML adoption for real-time SOC and SOH estimation are: (1) the inability of pure ML models to model battery aging mechanisms, (2) a wide variety of external EV operating conditions that affect battery degradation, and (3) the fact that most research work is conducted at the cell level rather than at the battery-pack level.[64]

Safety is a critical topic in battery applications and another operation of BMS is to minimize the risks of battery failure during EV operations, which can be life threatening in the case of battery-pack runaway.[80] Early battery-fault detection using ML approaches has seen recent development in EV battery-pack diagnosis.[81–83] Early detection of location, time, and cause of a battery cell or module failure in an EV

battery pack ensures user safety and EV longevity. Faults in battery cells can be caused by operational abuse (overcharge, overdischarge, and extreme temperature exposure), faulty external connections, and mechanical damage.[84,85] Although operational abuse can be overcome by having electrical charging controls and a thermal management system, EV battery packs are still prone to mechanical defects from operations, such as vibrations during trips. Traditionally, in BMS applications, the faulty battery location is determined by comparing the current battery-terminal voltage with its historical estimators (such as mean and standard deviation)[86,87] or voltage across the load[88,89] (Table 1). However, these approaches are not suitable for real-time EV applications mainly because the EV voltage profile during battery-pack charge and discharge is dynamic and nonuniform. It is interesting to note that the above-mentioned mechanical faults can be detected by changes in battery-terminal voltage and surface temperature.[85,90] DL algorithms have been successfully applied for voltage or temperature changes and for faulty battery time and location by using relatively low computational resources.[81,72]

In case of terminal voltages, statistical measures for variations between cell voltages (such as voltage differences and covariances) and within cell's historical voltages (such as rolling variances) can be used as inputs for DL algorithms. Specifically, the general regression neural network (GRNN) has been employed for fault detection with a high accuracy (>95%).[81] Meanwhile, when battery surface temperature (Figure 4D) in the battery pack is used as a fault indicator, RNN can be trained to predict the normal battery temperature. The prediction from this trained model can be used to compare the actual values for anomalies (Figure 4E).[72] Therefore, compared with traditional methods, methods based on DL are more applicable to potential real-time EV use because of its accuracy and ability to facilitate changing load profile during EV use. However, insufficient battery-pack-level datasets with a wide variety of operating and external conditions and incomplete battery-fault knowledge currently hampers the deployment of these ML algorithms for commercial purposes. Acquiring knowledge of battery faults requires experimentations with numerous experimental conditions and samples. Again, ML can be used to find trends between the cause and consequence of a battery fault by using datasets from experiments and physical models.[91–93]

ML in range optimization

Besides the battery-management technologies reviewed above, range optimization during EV driving can tremendously increase energy efficiency and save driving time. In general, range estimation (RE) is a step to achieve EV range optimization. As one of the most important research areas of EV today, an accurate RE can largely mitigate range anxiety faced by the EV drivers because of limited driving range.[94,95] EV drivers can make effective driving, parking, and charging decisions and participate in more vehicle-to-grid (V2G) charging. However, conventional RE methods are not always accurate mainly from its disregard of dynamically changing external and operational conditions.[96,97] For example, the range estimators in Tesla's Model S use the energy consumption of the past few miles to estimate the future available range, without considering changes in environmental, driving conditions, and behaviors.[94]

Compared with traditional RE methods, AI can provide opportunities for accurate RE by mapping the complex interaction between RE and the factors affecting it. Furthermore, AI algorithms, including ML, can be used to accurately predict the future environmental and driving conditions based on past and current conditions. These future predicted conditions can be used for a more accurate RE. Table 2 summarizes some

Table 2. Representative research of machine learning (ML) in EV range estimation (RE)

Approach	Parameters	ML algorithm	RE accuracy
Historical data	battery SOC voltage (min, max) current (min, max) temperature (min, max) vehicle speed (avg) external temperature visibility precipitation	significant parameter identification using correlation analysis followed by multiple linear regression (MLR)	1.63 km (MAE)[106]
		classification and regression tree (CART)	1.27 km (MAE)[98]
		gradient boosting decision tree (GBDT)	0.82 km (MAE)[98]
	battery SOC SOH vehicle auxiliary load weight external road type traffic temperature driving behavior	artificial neural networks (ANN)	2.2% (MSE) accuracy for a 50.4 km real-life EV trip[103]
Predicting future energy/power consumption	Vehicle speed recent energy consumption external road elevation	linear regression (LR)	2.18 km (MAE)[105]
		support vector regression (SVR)	1.95 km (MAE)[105]
	vehicle speed acceleration past power consumption past distance past trip run time temperature weight of loads tire pressure frontal area external road elevation	MLR	1.95 km (MAE)[104]
		principal component regression (PCR)	2.07 km (MAE)[104]
		clustering of data using self-organizing maps (SOM) followed by regression tree	0.70 km (MAE)[104]

Abbreviations are as follows: MAE, mean absolute error; MSE, mean-squared error.

of the relevant works in the literature for RE using AI. AI algorithms have been used for RE by directly using environmental and historical driving behavior data,[98,99] estimating the EV battery energy or power consumption,[97,100–103] and identifying driving conditions and behaviors.[97,104,105] For ML training, real-time historical discharge EV data are processed to extract relevant battery, and vehicle, and external parameters (Table 2) and to remove missing and erroneous data. Moreover, the EV historical data can be fused with historical weather, traffic, and road conditions to include external parameters, thereby increasing the RE estimation accuracy through ML training.[98–100] Parameters that have most impact on RE, such as battery SOC and external temperature, can be estimated by using correlations and are considered to reduce ML model complexity and training time.[98] ML models can be trained to output EV range directly, as well as the EV future energy or power consumption. By considering dynamically changing EV internal and external conditions in a computationally resourceful manner, and without use of complex explicit models, ML allows for an opportunity for more accurate RE.

The EV control system

The EV control system also plays an essential role in EV hardware's energy consumption and thus can indirectly impact the EV's driving range. Optimal EV control-system use ensures reduction in energy consumption of EV hardware including power steering, regenerative braking, and internal environment hardware controls such as HVAC (heating, ventilation, and air conditioning) while maximizing vehicle speed.[107]

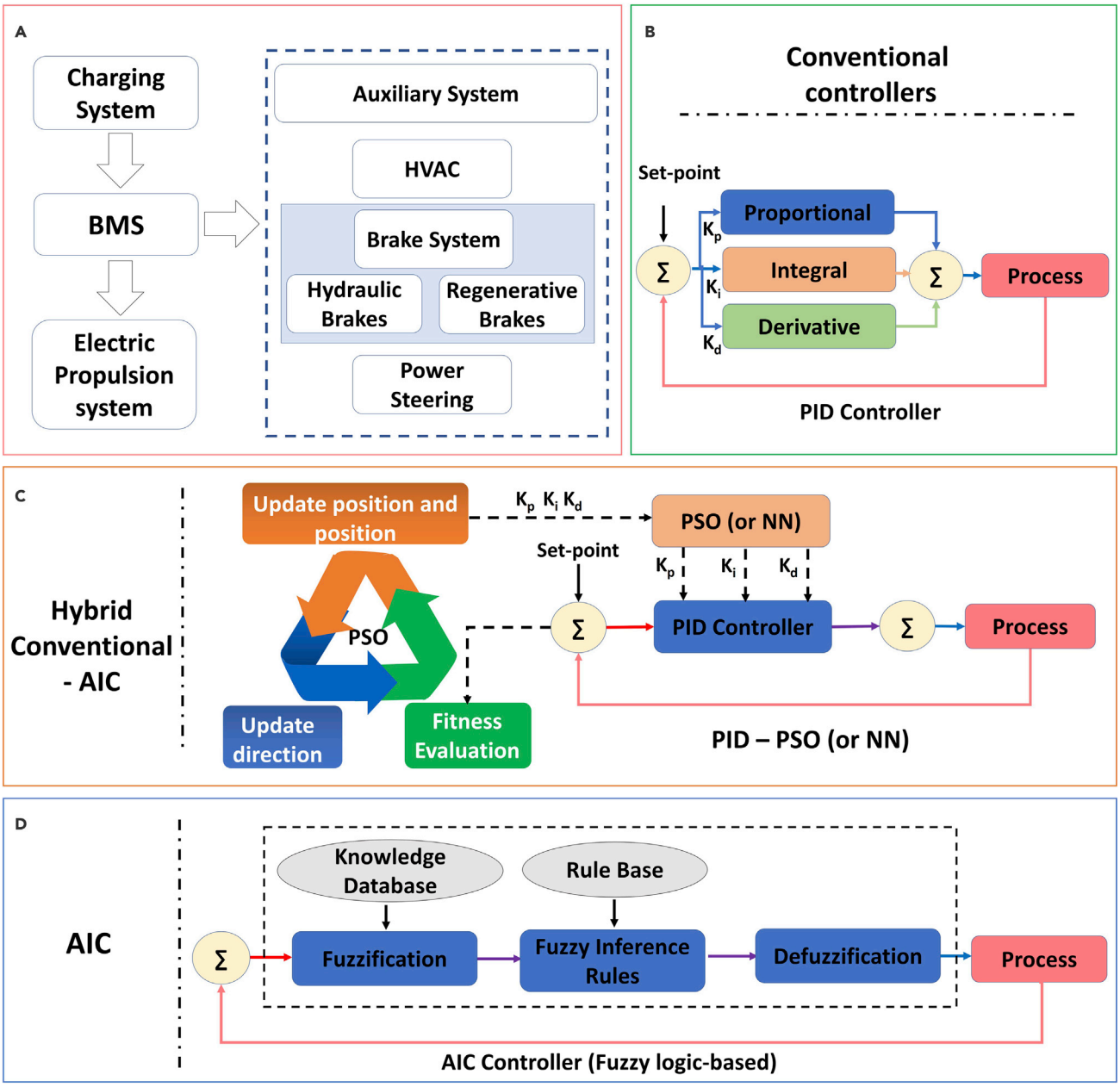


Figure 5. EV control architecture and process flowcharts of some related controllers
(A) EV control architecture.
(B) Conventional (PID) controller.
(C) PID-artificial intelligent controls (AIC) (particle swarm optimization [PSO] based) controller.
(D) AIC (fuzzy-logic based) controller.

Particularly, the regenerative braking system (RBS), available in most EV models, provides an opportunity for energy generation for increased driving range. The RBS converts kinetic energy into useful electric energy when the vehicle slows down, thereby extending the range of the EV.[108] Driving technique, system temperature, and ambient temperature affect the efficiency of energy extracted from RBS.[109] Figure 5A shows the energy flow and communications between different EV components including charging system, BMS, electric propulsion system, and auxiliary systems.

Control systems involve controllers that act to change the state or process of the system based on the inputs from the sensor readings. Artificially intelligent controls (AICs), involving AI techniques such as fuzzy logic, NN, and evolutionary algorithms, can be either used as a substitute for or in conjunction with conventional industrial controllers, such as proportional, integral, and derivative (PID) controllers (Figure 5B).[110,106] Among current optimization strategies for EV control systems, AIC, either exclusively or as an AIC-PID hybrid model, are researched as an emerging and smart choice for EV control-system design and optimization to improve the energy efficiency and further relieve range anxiety.[28,108,109,111–116]

As for hybrid AIC-PID controller, CI algorithms, including particle swarm optimization (PSO) and ant colony optimization (ACO), can be used to tune the critical parameters of proportional (K_p), integral (K_i), and derivative (K_d) parameters to further reduce the process steady-state error, overshooting.[117–119] A case in point is the PSO algorithm used in hybrid PID-AIC controller (Figure 5C), in which a predetermined number of random solutions (i.e., PID parameters) are initialized in the search space. Each solution is evaluated, compared, and updated with others to search for the optimal one. Similarly, ACO attempts to find the optimal path in the search space by having the solutions track their path. The optimal solution leaves the most intense pheromones trail, which influences the path of other solution. As a result, PID parameters tuned with PSO and ACO algorithms have been shown to aid in reducing the assisted current drawn by the electric power-assisted steering (EPAS), further translating into better EV energy conservation.[28] Furthermore, using NN to tune RBS PID controller has a positive effect on PID's response time, steady-state error tracking, and resisting perturbation, resulting in higher EV driving range.[115]

Regarding the AIC controller, a typical one is the fuzzy-logic-based AIC controller, which is also called a fuzzy-logic controller (FLC). As shown in Figure 5D, fuzzification is the process to convert numerical input signals into linguistic equivalents, and defuzzification uses rule-based inference, a linguistic output determined and transformed into a numerical output.[120] In the EV context, FLCs are deemed superior to conventional controllers in HVAC systems because they can effectively handle user comfort while reducing energy consumption.[111,121] Moreover, this reduction in energy consumption results in higher EV driving range when SOC and vehicular speed are used as FLC inputs.[111] Regarding the specific AIC applied in RBS, FLC and NN have been researched with respect to the braking allocation between regenerative and conventional hydraulic braking systems. This braking allocation ensures maximum energy generation while maintaining EV user safety. Braking (e.g., braking pedal displacement), battery (e.g., SOC and temperature), and vehicular speed can be used as FLC inputs to optimize the braking allocation for highest energy conservation.[112–114] When tested on a prototype EV, the FLC system showed an improvement of 16 %, 22.2 %, and 25.7 % in motor efficiency, energy efficiency, and maximum driving range, respectively, compared with that of the nonfuzzy RBS.[114] However, for real-time EV applications, it is important that the hyperparameters of NN are optimized for functionality and processing speed.[122] Alternatively, the FLC can trigger the RBS motor in case of driver coasting or creeping behavior, when representative FLC inputs, such as the stokes of the acceleration and braking pedals, are used. Results from the simulations and hardware-in-the-loop tests demonstrated a higher energy regeneration and braking stability.[116] Although in FLC rules are clearly defined, the construction of these rules is nonobvious, difficult, and requires expert knowledge. In such a case, AICs based on CI algorithms can be used to ease the control design and performance.[122]

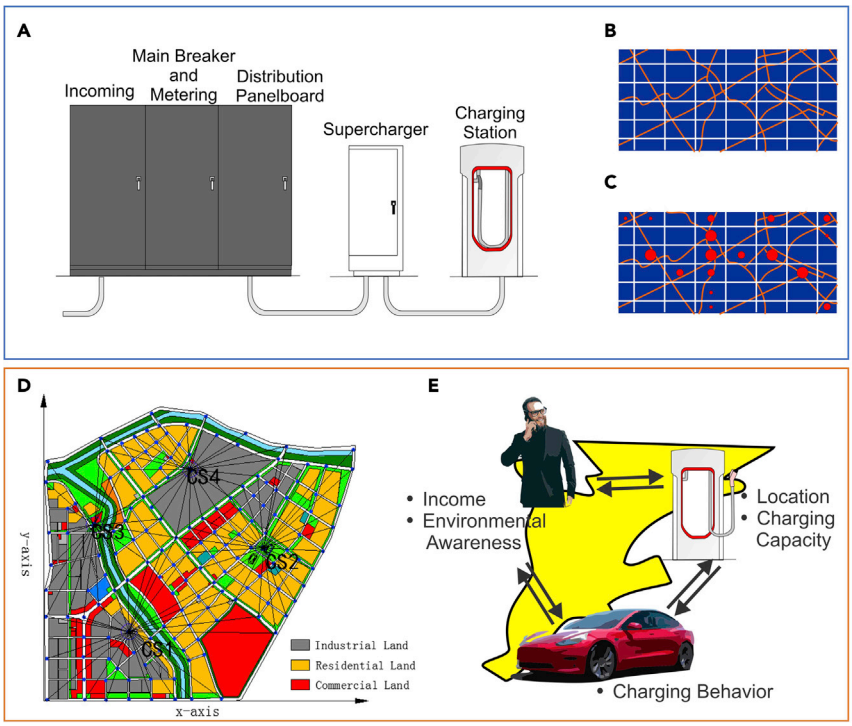


Figure 6. Cases for optimal placement of electric vehicle charging stations (EVCS)

(A) Tesla superchargers consisting of distribution panelboard, metering, and incoming power source.[123]

(B and C) Clustering of spatial map based on traffic density and EV driving distance. For traffic-density distribution, the traffic data of road segments within a predetermined grid are aggregated and overlaid on the corresponding grid. As shown, the traffic density is pictorially represented by the radius of the red circle. For driving-distance clustering, the regions on the map are clustered based on the location of EV and its destination points.[126]

(D) Objectives of EVCS are modeled by using as a MOOP problem, which is solved by using CI algorithms (PSO)

PSO was used to solve for MOOP, which considers land-cost and distribution investments; meanwhile running cost was considered as the restraint. Solutions of PSO lead to Pareto solutions of optimal EVCS placement. Reprinted with permission from Awasthi et al.[127] Copyright 2017 Pergamon.

(E) Agent-based modeling for EVCS optimal location. In this example, the agents (EV owners, EV drivers, and EVCSs) are placed in a geographical environment and their attributes (mentioned in the figure) are modeled. The two-sided arrows represent the interactions between the agents.

AI IN ELECTRIC VEHICLE CHARGING STATIONS (EVCS)

Prediction of the optimal location

One of the important ways to reduce the EV user range anxiety is the optimal placement of EVCS, namely the optimization of charging locations. This placement will give the user more confidence in using an EV, given that the user has a higher chance of finding an EVCS before the EV battery dies. EVCS are classified based on the charging voltage provided by the charger, and these categories are Level 1 (120 V), Level 2 (240 V), and DC fast charging (about 400 V in case of Tesla supercharging stations) (Figure 6A).[123,124] To gain wider EV acceptance and provide user convenience, Tesla has installed about 1,971 DC fast charging stations globally. Level 1 EVCS, with long charging times, are usually placed in parking lots, wheras DC fast EVCS are placed near high-volume road access points. Another company is ELaadNL, which is one of the largest Dutch EV-infrastructure providers, provides optimally placed charging spots throughout the Netherlands and

promotes the use of data analytics, including the use of ML, to plan for EV infrastructure.[125]

Optimal placement of EVCS depends on several factors, such as the local charging demand, construction feasibility, road network and other infrastructure, operating economy, and power-grid security.[128] Optimal placement of EVCSs is generally formulated as a multiple objective optimization (MOOP) function with objectives comprising minimization of costs, maximization of net present value (NPV), or preference to unpopulated areas.[126,127,129–133] The cost function, which is beneficial for the EVCS owner and from the policymaker's perspective, includes the costs of EVCS construction, operations, and charging.[127,134,135] The total costs of EVCSs are formulated into annual costs by considering the expected total time of EVCS operations and market interest rates.[134] NPV, an economic evaluator, discounts future cash flows from a project (an EVCS project in this context) and, together with the costs, indicates the economic feasibility of the EVCS project.[136] Therefore, maximization of NPV and minimization of total costs of an EVCS project are crucial for policymakers, investors, shareholders, and owners of the EVCS projects. Moreover, Pevec et al. examined the objective function, which gives EVCS placement priority to locations where there is a smaller number of existing charging stations.[129] By populating EVCS in low EVCS densities, the convenience of EV charging for EV owners in these areas is enhanced, and the local municipal government's objective of EVCS installations are met. The primary purpose of optimal placement using MOOPs is to identify optimal EVCS placement that satisfies the objective function.

ML is used for preparation of data or models for these MOOPs,[129,126,137] and CI, including swarm intelligence (e.g., PSO) and evolutionary algorithms (e.g., GA) can be used for solving these MOOPs.[127,130–133] At the data and model preparation stage, supervised ML models, as opposed to mathematical models, can be trained on a dataset containing data on existing real-time EV operation, traffic, and EVCS operations, and hence, the predictive ability of this approach is more in tune with real-world scenarios. As for the latter, in CI, the use of evolutionary computing algorithms for solving charging-station placement problems has also been widely investigated.[133] The solution approach for optimal placement of EVCS can be divided into three main steps, which include data collection (Figures 6B and 6C), data preprocessing, and placement improvement. ML clustering algorithms, such as hierarchical or K-means clustering, can be used to form zones, within a geographical context, based on the typical EV driving distance and destination locations.[129,126] In the second step, ML methods are used for modeling EV user demand and traffic occupancy, which are subsequently used in MOOP.[30,129] When it comes to the third step, optimal placement is determined by solving for the MOOP by using CI algorithms such asas PSO[127] and GA[130] (Figure 6D).

Aside from the MOOP relevant approach, ML can be used for optimal EVCS site placement without formulating a MOOP. This approach removes the calculations required in the MOOP case, which allows for the inclusion of qualitative data, removes underlying models and corresponding assumptions, and possibly removes the computational load required for MOOP.[138] EVCS placement without MOOP has been solved by using supervised ML algorithms such as K-means clustering,[137] Bayesian networks,[138] and NN.[135] In these models, where ML models are exclusively utilized, the ML models are trained on real-life datasets and output the preferred EVCS location. Hence, despite the stated advantages of this approach over MOOP, a large dataset is required to ensure model robustness and reliability.

Another research approach to determine EVCS placement and sizing is through agent-based models (ABM). In this approach, different agents (such as EV owners, EV drivers, and EVCSs) are assigned different attributes and interact with each other in a model environment within a geographical location (Figure 6E).[139–141] Despite ABM's complexity and higher computational demand compared with MOOP, it allows for a more realistic modeling tool by considering different agents, their attributes and their complex interactions.[141,142] Furthermore, the agent's attributes, such as the charging behavior of the EV driver, can be modeled with stochastic processes to account for different possible real-life scenarios. Within the context of EVCS placement, ABM has been used to model and study the short-term and long-term impact of EVCS placement and charging capacity on EV adoption and charging use, which allows for EVCS roll-out strategies.[139] ML techniques, both supervised and unsupervised, can be implemented in ABM to improve model accuracy by modeling agent behavior and decrease the computational demand.[143,144] With the advent of charging datasets (publicly available from ElaadNL[145] and CAN-Data[146]), the EV owner's charging behavior can be modeled by using supervised and unsupervised ML algorithms, including DL.[147] Furthermore, the ABM's input (the agents' inputs, attributes, and interactions) and output can be trained and subsequently modeled by using supervised ML algorithms, which reduces the overall computational load requirement and aids in the ABM model's understanding by replicating the nonlinear behavior.[143,148]

Energy scheduling and congestion management

Compared with building new infrastructure, which requires significant planning, investment, and legal agreements, another energy- and time-efficient approach to increase consumer interest in EVs is the efficient use of existing EV-charging infrastructure. Accordingly, AI-based routing algorithms can be used to further improve the efficient use of existing infrastructure such as EVCSs via energy scheduling and congestion management. Therefore, this section deals with the AI application in strategies that aim to improve resource- and usage-efficiency, while considering user comfort and convenience. Specifically, energy forecasting and management, congestion reduction, and fast and smart charging within an EVCS are mentioned.

For the EVCS to smoothly operate within the energy constraints of the local grid, it needs to balance the EV-charging demand and available load supply. Hence, it is important to predict the energy and charging demands of EVCSs and to use the energy resources efficiently. The steady penetration of EVs in the automotive industry has led to the availability of user EV-charging data. ML approaches on this EV data combined with other temporal (e.g., temperature) and geographical data (e.g., points of interest) can lead to a more realistic and accurate EVCS energy and charging demand estimation. Furthermore, compared with the traditional deterministic approach to energy determination, the ML-based approach accounts for uncertainties resulting in real-world charging applications by using relevant historical datasets.[149] Within this context, ABM can be used to identify EVCS capacity on the basis of available energy resources, availability of EV drivers, and their charging behaviors.[139,150,151] ML algorithms, including linear regression[152] and NN,[153] can be used to predict the charging behaviors of EV consumers and estimate the energy demand.[152–156] ML methodologies used in these works are general and applied to any specific geographical location for accurate EVCS demand and charging predictions.

For EVCS user convenience and comfort, it is important to reduce the queue and charging times. It is worth noting that, even with fast DC charging, it takes 30–60 min to charge an EV fully, whereas it takes minutes to fill the tank in a traditional

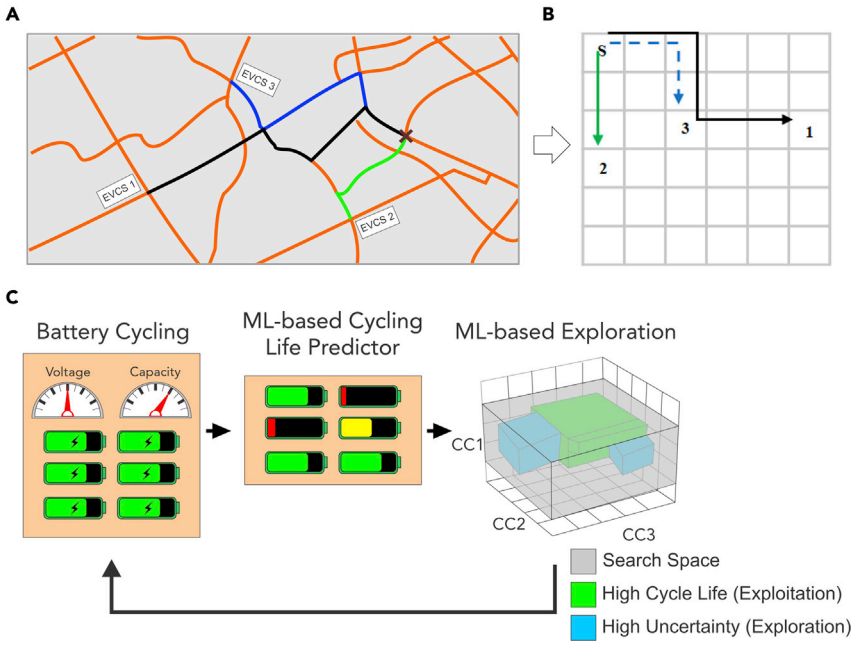


Figure 7. Examples of EVCS congestion management using RL and smart charging using ML
(A and B) RL for congestion management. The map of three EVCS is mapped into a grid where each EV starts from the same starting point and the relative distance of EV to EVCS is maintained. Furthermore, the traffic density of the road segment is mapped onto the individual grid. The RL algorithm optimizes the congestion policy to minimize the total EVCS waiting time.[157]
(C) Bayesian-based ML model for fast-charging protocol
In this iterative ML-based charging protocol, the outcome of the battery is determined by using a predetermined ML algorithm. Based on this early outcome prediction, the Bayesian optimization determines the next charging outcomes for successive cycles in the four-stage MCC charging protocol. The Bayesian-based ML algorithm, along with the ML-based early-life predictor, finds the charging protocol, i.e., the C-rates, for the first three cycles.[54]

internal combustion engine vehicle. Therefore, an additional EV in a fully occupied charging station can add the waiting time for other cars in the queue for about half an hour. The use of supervised and unsupervised learning in congestion management in EVCS placement is limited because of a lack of limited relevant EVCS datasets. As a potential solution, RL can be used for appropriate policy determination to schedule EV to relevant EVCS to minimize wait times (Figures 7A and 7B).[157]

Apart from congestion management, AI algorithms are used for the determination of optimal charging protocols without compromising safety and EV battery-pack life in academic and commercial research.[158–160] The common charging modes include constant current–constant voltage (CC-CV) and multi-stage constant current (MCC). In CC-CV, the batteries are charged to cut-off voltage at a constant current and then maintained at cut-voltage. Meanwhile, batteries are charged in intervals in MCC, where different currents are supplied at different time intervals. The current is held constant within a time interval. In the research community, MCC is a popular choice for fast charging, and the research efforts are focused on determining the best current and time intervals for charging.[161] It would be extremely time consuming to test for different numbers of charging time intervals and the combinations of charging current for these time intervals by using physical experiments. As an alternative approach, the charging current for each time interval can be formulated as using a model, which can be solved by using evolutionary algorithms.[162–166]

More recently, Attia et al. used ML for current determination for the fast charging of lithium-ion batteries while setting the number and time of charging stages. An early detection model, that can predict the lifetime of a lithium-ion battery from initial cycling data, was followed by a Bayesian optimization algorithm to probe into the possible search space (Figure 7C). As opposed to searching for C-rates for each charging step, Bayesian optimization was used to find promising C-rates, of the first three cycles of the MCC, based on results from the iterative process. The C-rate of the fourth cycle is dependent on the first three cycles. As a result of this approach, significant time- (560 versus 16 days) and cost savings were achieved when compared with brute-force search because this ML-based approach optimally searches the promising C-rates from the entire search space.[53,54]

AI IN THE INTEGRATION OF EV WITH THE SMART GRID

Introduction and main challenges of the integration

Smart grids, in comparison with the traditional electric power distribution systems, allow for two-way energy flow, secure dynamic optimization of energy flow operations—such as determining the pricing of charging an EV based on the supply and demand of electricity—and smoother integration of renewable-energy production and storage.[167–174] The direction of energy flow from the grid to EVs is referred to as grid-to-vehicle (G2V), in the case of EV charging, and vehicle-to-grid (V2G) in opposite energy flow.[175] Therefore, from the smart-grid perspective, the EV can be viewed as energy storage during charging in G2V and potentially an energy generator during its discharge to the grid in V2G. As shown in Figures 8A–8D, this bidirectional energy flow allows for an efficient grid-energy generation and distribution through frequency regulation, peak shaving and load leveling (Figure 8B), load regulation (Figure 8C), and spinning reserve (Figure 8D), particularly in the case of grids wholly or partially powered by intermittent sustainable energy sources such as solar and wind.[175–177] Furthermore, this attractive feature of energy generation to the grid can be a revenue stream for an EV owner, and V2G technology has also garnered major industrial interest.[178]

On the other hand, regardless of the advantages and benefits, V2G and G2V also face several technical, economic, legal, and social challenges, which include social resistance to V2G, energy distribution complications, hardware barriers, and high investment cost.[175,179] One typical challenge is the scheduling and distribution of the smart grid with EV, which is complex because it requires considerations of several, and often conflicting, objectives and restraints, including lower operational costs, maximizing profits for power-generation plants and EV owners, minimizing carbon emissions, and matching the real load curve with the target load curve. To deal with those challenges, AI can be used as an effective tool. Specifically, AI algorithms can regulate the energy scheduling and optimization problems resulting from the complex two-way interaction between the EV aggregates and renewable-energy generation systems. Moreover, AI can be also instrumental in ensuring smooth power distribution considering renewable-energy generations' intermittency.

Optimization of power generation and distribution

Power generation and distribution are restrained by meeting the load demand and supply, power-generation limits, voltage bounds, and power line thermal capacity. To optimize power generation and distribution by consideration of those restraints, both CI and ML have been investigated and applied as an effective strategy. As for CI, the restraints can be first formulated as MOOP,[29,175,180–183] and further solved by evolutionary computing algorithms, which can handle multiple nonlinear MOOPs with multiple restraints using reasonable computational hardware and software.[175] For instance, Soares et al. optimized V2G and G2V scheduling by formulating a

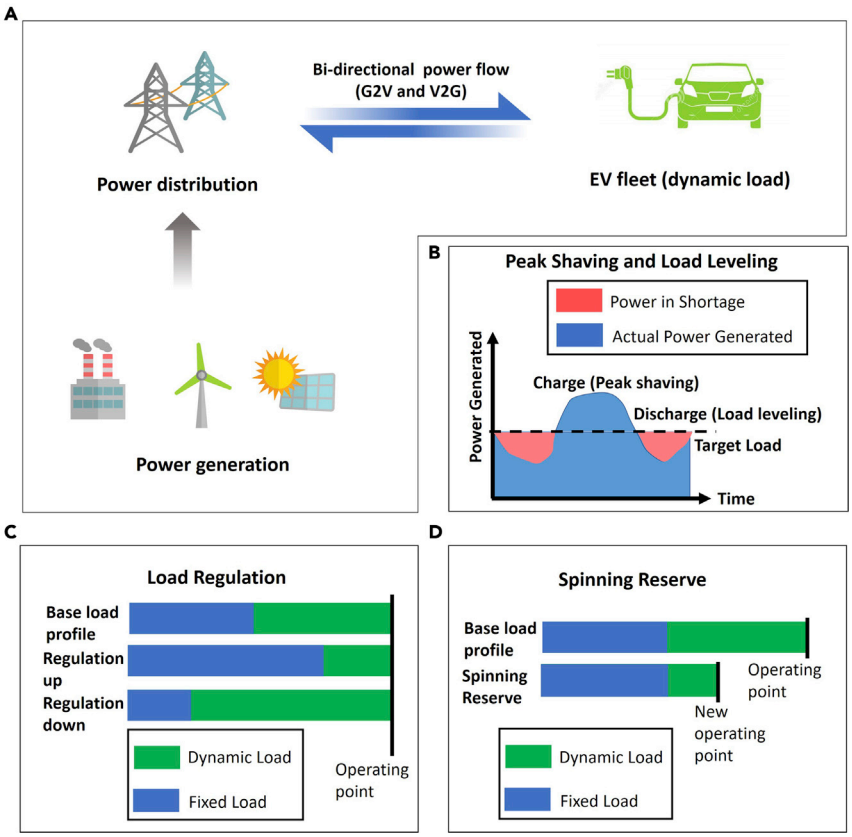


Figure 8. Integration of V2G with the grid and its effects on peak shaving and load leveling

(A) Bidirectional energy flow between smart grid and EV. Grid-to-vehicle (G2V) and vehicle-to-grid (V2G) technologies allow for bidirectional flow of power between the EV and the grid. EV cab utilizes the power from the grid when charging its batteries. Moreover, when EV is not being used and has excess power, it can transfer that power to the grid. Moreover, this bidirectional power flow can be integrated with the renewable-power generation systems to ensure sufficient power is available in the grid.

(B) Peak shaving and load leveling. Batteries in the EV can be used as energy storage to ensure target load is achieved in the grid. EV batteries can be charged at times of high power generation which can be used at a later time to supply power to the grid at times of low power generation.

(C) Load regulation. The load profile can be regulated up and down to ensure that the same loading is achieved. The EV can be considered as a dynamic load when it is charging. When the fixed load is increased, Ev charging can be reduced (by increasing the power cost, for example) as in the case of regulation up. In the opposite case of reduced fixed load, EV charging can be encouraged.

(D) Spinning reserve. In case of power outrage, addition power (spinning reserve) can be employed to compensate. The dynamic load, which includes EV charging, can be reduced, which in turn reduces the overall load.

MOOP to minimize total operation cost while maximizing the revenue obtained by EV users. The demand and supply load matching, power generation, voltage and thermal limits, and EV-charging limits were considered constraints. A Pareto front of the MOOP in a simulation case study with a 33-bus distribution network and 1,800 EVs was solved by using PSO with good convergence.[29] Additionally, Su et al. solved an operational cost minimization objective function with the restraints considering reducing EV battery life and EVCS queue waiting time. The former restraint was related to a battery-cost model that considers the battery SOC, and the MOOP was solved by using an artificial fish swarm algorithm (AFSA). The model's optimized parameters were able to reduce the cost of battery degradation by 80% and queue wait time by 60%.[182]

Aside from CI, ML can also be used in optimization of power generation, scheduling, and distribution. A case in point was investigated by Yang et al., who formulated an MOOP to minimize system power fluctuation and battery degradation, in which the battery lifetime model is based on a DL algorithm, specifically LSTM, a type of DL algorithm. Simulation results based on microgrid data in Belgium demonstrated the algorithm's ability to reduce both system power fluctuation and required EV charge-discharge cycles for V2G.[183] Moreover, Shipman et al. used ML-based mode by using factors affecting users' decision to participate in V2G and their reliability in following through with their decisions. EV user availability and location were tracked by using an app and formed the model inputs. The model was able to predict an EV fleet's availability at a charging spot for each hour during 4 weeks with an error rate of only 5%. This prediction model is paramount in estimating the available storage capacity.[184]

Optimization of renewable energy relevant systems

Similar energy management and optimization approaches can be applied to systems with renewable-energy generation systems, such as solar and wind power plants. The electrochemical storage capability of EVs can in particular be used for load shaving and load leveling due to intermittent power generation from renewable-energy sources.[175–177] Here, example research works on the integration of V2G with the power-generation grid with renewable-energy sources are presented. Soares et al. used PSO to solve for a MOOP to minimize operation cost and maximize EV owners' profits. In a case study with a 32-bus distribution network and 50 plug-in hybrids, PSO demonstrated to be 148 times faster than mixed integer programming linear programming.[185] Additionally, Liu et al. solved a MOOP by using PSO to minimize the power grid operators and EV users' cost, global CO_2 emissions, and wind curtailment when coordinating EV charging and discharging activities with the power grid of thermal plants and wind farms. The best results from the Pareto front were determined by using decision-based fuzzy rules. Their results showed that the EV discharging coordination at peak power loads with low winds could curtail CO_2 emissions.

Furthermore, EVs charging during times of low demand and high winds can reduce the wind curtailments.[180] To minimize the high variations in wind-energy generation, Ghofrani et al. used GA and Monte Carlo simulations to coordinate the charging and discharging behavior of EV fleets, based on their daily driving habits. Based on the EV hourly data regarding parking time and distance, the EV fleets are grouped into 6 categories. In conjunction with Monte Carlo randomness in search procedure, GA is used to solve for the MOOP on costs of wind imbalances and V2G expenses. The simulation results on an EV fleet of 484 and a 10-MW wind-power station show a significant merit in using V2G compared with gas-powered generators and battery systems to offset the wind-power imbalance.[186]

CONCLUSIONS

Key summary

Mass EV adoption is considered a necessary step toward decreasing global reliance on unsustainable energy sources and reducing emissions detrimental to the environment. Recent years have seen wide commercial and academic research efforts to overcome the challenges to EV adoption and make EVs attractive to consumers. This review focuses on those efforts where AI has been applied, including the related areas of EVs, EVCSs, and the interaction of EVs with the smart grid, in which commercial interest in these areas have been summarized and even highlighted. Specifically, AI algorithms used in EV battery design and discovery, battery management, and

accurate RE, and the role of AI in the smart control of EV hardware and auxiliary systems to conserve battery energy. In the subsequent section, AI in optimal location and energy usage of EVCS is discussed with consideration to EV user charging convenience and comfort. Finally, the AI role in the complex energy management and optimization problems in V2G applications are reviewed.

Outlook

Overall, current research and practical commercialization of AI in EV and related infrastructure are still in the early stages of development. Some areas of EV, where AI is used are already being commercialized more than others. It seems that the technical maturity of those techniques is sufficient to meet the requirements for practical implementation. To overcome current challenges, such as high-throughput data generation, performing *in situ* calculations, and the scalability of data from battery-level to battery-pack scale, and further facilitate the development of AI techniques used in EV and related infrastructure, some future orientations are provided below.

AI to further enhance the processing capacities of battery management, battery disposal, and energy controls

The processing capacity of the BMS is one of the limitations of using AI for real-time battery-state estimation (SOC) and diagnosis (SOH and early fault detection). In practice, BMS design uses embedded microprocessors for computations.[86] However, with advancement in embedded systems from Moore's law and scalability of ML algorithms,[25] ML-based approaches would be expected to be used for practical real-time EV applications. Additionally, BMS computations relating to SOC, SOH, and fault detection can be computed remotely on a cloud computational server, which alleviates the computational burden of BMS microprocessors.[93,187] Moreover, ML model training on battery-state estimation and fault detection have been conducted on small and specific datasets by research communities. This training on small datasets results in model that tends to retain that specific dataset instead of the underlying relationships. Implementation of such insufficient ML models on commercial levels can have dire safety consequences, such as failure to detect potential thermal runaway. As EV battery-operational datasets become more available with increased EV use, there is an opportunity to research and implement battery-pack-level ML models for real-time EV applications. To understand the underlying mechanisms, identification, and detection of faults in batteries, iterative experiments followed by ML for parameter exploration and exploitation can be conducted.[93] Furthermore, EV manufacturers can include ML-based fault detection algorithms that continuously learn from historical EV data periodically, which can effectively consider specific EV users' driving habits, common driving conditions and external conditions (e.g., weather conditions).

Another potential risk of using AI in EV battery-management and control systems is related to user privacy violations.[188] As more AI algorithms are used in EVs, user data—for example, driving habits and frequently visited locations—would be collected and stored by EV manufacturers or other third-party vendors. Potential EV users might be hesitant to share such information and this hesitance can lower the overall EV appeal to the population. Also, this mass data sharing and storage adds pressure for EV manufacturers.

Interestingly, another potential of AI approaches for remaining-useful-life (RUL) estimation can be used for battery waste and disposal. Higher sales and consumer interest in EVs raises a concern for the battery waste.[189] A report from the National

Laboratory of Renewable Energy (NREL), a US federal laboratory, identified a promising application of second-hand plug-in hybrid (PHEV) battery packs in grid energy peak shaving.[190] AI algorithms have been researched for the estimation of RUL[14,191] and can be applied to estimate the usage of disposed batteries before reconditioning for second-hand applications.

Challenges and perspective for AI in EVCS and EV integration with the smart grid

Most of the approaches discussed in this review for the optimal EVCS location and energy management require a model for energy demand and supply. This is a complex model with factors with high uncertainties, such as the charging patterns of EV users, which can challenge the model empirically or mathematically. Moreover, sometimes it is desirable to assign qualitative metrics for some factors when sufficient quantitative information is missing, such as quality of air. ML algorithms can be used in such cases but are challenged by the lack of sufficient EV user charging data. As the EV penetration in the automotive industry increases, this EV user charging data can become more accessible. CAN-Dataset is one of the publicly available EVCS charging datasets, which has data points on charging sessions from various on-site charging infrastructures.[192] Moreover, the approach of using RL and deep learning for load prediction in the smart grid has been deemed more commercially viable than that using traditional ML techniques.[193] It is also worth noting that due to high investment, legal and political barriers, and the actual construction and operation of EVCS at theoretically determined optimal EVCS site location might face considerate obstacles and, therefore, hinder its actual implementation.[194,195] Meanwhile, the discussed methods for improving and upgrading the existing EVCS infrastructure might hold considerably higher commercial merit.

The development and maintenance of EVCSs and other EV-charging infrastructure will have to keep on pace with the growing EV fleet.[196] Apart from optimal site placement of EVCS, ML provides the accommodation of EV-charging demand by the existing EVCS infrastructure through EVCS congestion management and demand-dependent pricing.[157,197] By estimating the electric demand for the EVCS by using ML models, utility and EVCS owners can dynamically change the pricing or charging sessions to curb or encourage EV users and ensure EVCS economic viability.[197] Recently, Valogianni et al. introduced adaptive pricing, whereby the prices are adjusted based on EV users' price reactions, and this pricing outperforms conventional pricing schemes.[198] ML models can be ideal candidates for future adaptive pricing because of their ability to model the complex interaction between EV users' behavior, external conditions, and price changes.

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AUTHOR CONTRIBUTIONS

M.A. and Y.Z. conceived the review article. M.A. conducted relevant literature reviews and wrote the original manuscript. Y.Z. did major revisions and conducted literature review accordingly. H.F. conducted relevant literature review and wrote part of the section on battery-management systems. A.A edited and proofed the manuscript. M.A., Y.Z., A.A., and Z.C. discussed, reviewed, and revised the manuscript. Z.C. and Y.Z. provided supervision throughout the manuscript-writing

process. M.A. and Y.Z. contributed equally to this work. All authors approved the final version of the manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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