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REVIEW

A survey on design optimization of battery electric vehicle components, systems, and management

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Abstract
This paper presents a comprehensive survey of optimization developments in various aspects of electric vehicles (EVs). The survey covers optimization of the battery, including thermal, electrical, and mechanical aspects. The use of advanced techniques such as generative design or origami-inspired topological design enables by additive manufacturing is discussed, along with sensitivity studies of battery performance with alternate materials and incorporating sustainability considerations. Strategies for battery charging/discharging and battery swapping are reviewed, taking into consideration factors such as operation, cost, battery performance, and range anxiety. Future research is suggested to address uncertainties in charging ecosystem design and incorporate both forward and inverse prediction capabilities, leveraging benefits for both the grid and individual vehicles. The optimization techniques for other EV components, such as motors, powertrains, tires, and chassis, are also discussed. Finally, this paper presents a review of the EV management, specifically the optimization of charging station, grid, and fleet management, including research on charging station construction, charging station operation strategies, and power system operation strategies. The need for further research on robustness, reliability, and sustainability is emphasized to justify the use of EVs in the future.

Keywords Battery electric vehicle · Component design optimization · Management strategy optimization · System optimization

1 Introduction

1.1 Review motivation

The automotive industry faces increasing environmental challenges, prompting a surge in research on electric vehicles (EVs) that is expected to continue. A comparative study examining the life cycle assessment of Electric Vehicles (EVs) and conventional fuel engine vehicles reveals a noteworthy finding: during operational use, EVs exhibit approximately 50% lower greenhouse gas emissions compared to conventional vehicles. However, when evaluating the manufacturing phase, EVs surprisingly demonstrate significantly higher emissions than their conventional counterparts. EVs present promising potential in reducing greenhouse gas emissions compared to traditional vehicles (Tagliaferri et al. 2016; Hawkins et al. 2013). Nevertheless, the manufacturing phase remains a substantial obstacle to the overall environmental performance of EV technology. Addressing this challenge necessitates extensive foundational research. Future advancements in energy sources and technological efficiencies have the potential to mitigate emissions during the manufacturing phase of EVs, thereby narrowing the gap between EV and conventional vehicle manufacturing emissions. To produce EVs with high performance, energy efficiency, and low cost, design optimization studies have been conducted at both the component and system level. However, while literature reviews exist on various aspects of EVs, such as life cycle assessment, architecture and topology development,

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control, infrastructure planning, consumer preferences and awareness, there is a lack of review on design optimization studies conducted for EVs (Hoque et al. 2017; Gabbar et al. 2021; Safayatullah et al. 2022; Unterluggauer et al. 2022; Liao et al. 2016). Therefore, this paper aims to provide an in-depth review of such studies and suggest future research areas.

Presently, both industry and academic sectors contribute to advancing battery design and optimization, but they often have different goals, approaches, and perspectives. Frith et al. (2023) published a paper on industrial aspects. It is mentioned that academic researchers usually operate on a lower technology readiness level so they are less concerned with or unexposed to end-user requirements or criticalities that need to be considered when scaling up and manufacturing an energy storage device. Batteries in a research laboratory are often tested using conditions and parameters far from commercial devices. Within the battery industry, there have been several high-profile examples of companies investing in over-hyped technologies which failed to meet the promised performance were also mentioned by the paper. Industrial entities, including battery manufacturers and technology companies, prioritize battery models that can be applied in real-world products. They focus on models that can help design and optimize battery packs for specific applications like EVs or energy storage systems. Industrial entities often rely heavily on proprietary data from their own battery manufacturing processes and field performance data. These models aim to predict battery behavior under specific conditions and usage patterns. These models prioritize cost-effectiveness and efficiency in their modeling efforts. This means finding practical solutions that can be implemented at scale within budget constraints. Whereas academic institutions have been focusing on fundamental understanding and scientific advancements.

Researchers in academia develop complex, physics-based models that explore the underlying electrochemical processes in batteries and promote open-source battery modeling tools. Academic researchers may take a long-term view, exploring cutting-edge ideas that may not have immediate commercial applications. Cao et al. (2019) talks about some of the most important testing factors that are frequently disregarded in academic literature but are essential for real-world use outside of the lab. There were explanations for metrics including anode energy density, voltage hysteresis, mass of non-active cell components, and anode/cathode mass ratio, as well as suggestions for future reporting. Though the perspective on the subject of industry and academia complement each other but due to the unlike mindset and goals, there are some gaps and challenges. Regarding the battery models, industrial entities require models that are rigorously validated and verified under various operating conditions and across different battery chemistries. Academia may lack access to proprietary industry data, making it challenging to develop models that are directly applicable to industrial systems. Industrial models prioritize computational efficiency, as they need to run in real-time or near real-time for practical applications while on the contrary academic models might be computationally intensive since they focus on the quality of the solution.

1.2 Challenges in design optimization of electric vehicles

Design optimization of EVs poses significant interdisciplinary challenges, including power management and optimization, system integration, vehicle dynamics and control, drivetrain systems, chassis design and layout, and electrification of automotive systems. Key challenges in EV design include limited driving range and battery degradation, insufficient charging infrastructure, and uncertain powertrain component performance under varying environmental conditions such as temperature variation and mechanical shocks. EVs require simultaneous optimization of various components, including batteries, powertrain, electric motors, body and chassis, suspension system, and tire, under uncertainties as shown in Fig. 1. Furthermore, optimization must also be considered at various levels, from the battery cell level to the system level, making design optimization of EVs numerically challenging (Un-Noor et al. 2017; López et al. 2019; Ghosh 2020; Haram et al. 2021). EV optimization includes component optimization that deals with the shape of components, management optimization that deals with the operation of components, and system optimization that deals with the external system of EV. This paper aims to review existing literature that addresses these challenges in design optimization of EVs.

1.3 Paper organization

The remainder of the paper is organized as follows. Section 2 provides a review of thermal, electrical, and mechanical optimization studies for EV batteries, covering battery cell thermal management, battery liquid/air cooling, battery charging strategies, and mechanical optimization. Section 2 is related to the thermal system (cooling), power electronic controller, charge port, and traction battery pack in Fig. 1. Section 3 reviews design optimization studies for other EV components, such as powertrain, motor, body and chassis, suspension system, and tire. Section 3 relates to transmission, electric traction motor, chassis, and tires in Fig. 1. In Sects. 2 and 3, design variables, constraints, and objective functions are organized in a table according to the following general optimization formula.

$$Minimize\ :\ \left(f_1(x), f_2(x)\ \dots, f_n(x)\right)$$

$$s.t.\ :\ g_i(\mathbf{x}) \leq \mathbf{0}, \mathbf{i} = \mathbf{1}, \mathbf{2}, .., \mathbf{m}; \# \tag{1}$$

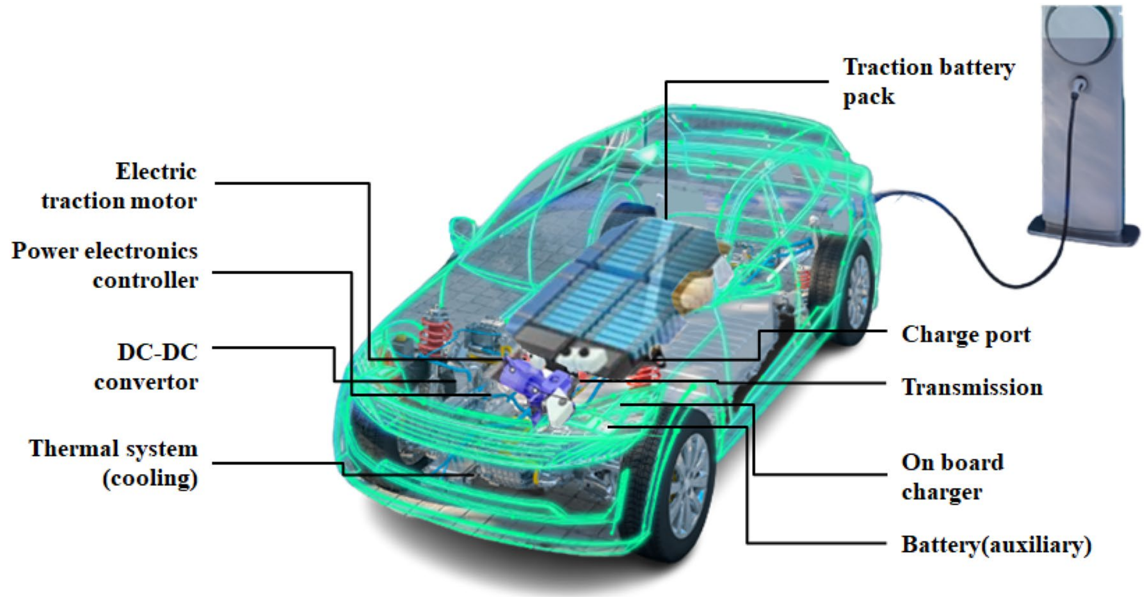


Fig. 1 General EV with main components (Image skeleton courtesy of Siemens Digital Industry Software)

$h_j(\mathbf{x}) = 0, \mathbf{j} = \mathbf{1}, \mathbf{2}, .., \mathbf{l}$

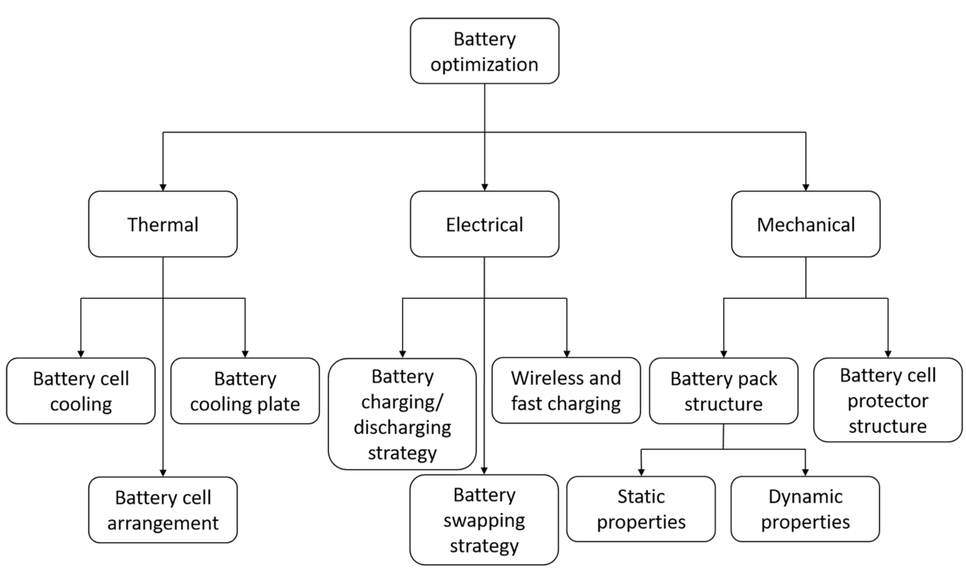
Section 4 focuses on design optimization studies for EV management, including charging stations, grid management, and fleet management. Finally, Sect. 5 concludes the paper with remarks on the current status of design optimization of EVs and suggests future research directions.

2 Optimization of battery in EV

The battery is one of the most critical components of an EV, consisting of battery cells that are combined to form a battery module, which in turn is combined to form a battery pack. The battery has a significant impact on the effectiveness and performance of EVs, leading to numerous studies being carried out to enhance its power, efficiency, and stability.

Figure 2 presents the broad classes of battery optimization, which include thermal, electrical, and mechanical

Fig. 2 Overview of EV battery optimization object



optimization. Thermal optimization aims to maintain a constant temperature of the battery cell while transporting heat to the outside. This can be achieved by adjusting the configuration of battery cells or designing a cooling component. Electrical optimization focuses on making the battery's charging and discharging process more efficient, with a specific emphasis on the battery's electrochemical characteristics. Mechanical optimization typically aims to increase the battery's mechanical stability, accomplished by choosing the structure of the battery pack or the shape of the battery cell protector as a design variable. In the following sections, we review the literature on optimization for each aspect discussed above.

2.1 Thermal optimization of battery

Section 2.1 discusses various thermal management techniques as shown in Fig. 3 used to dissipate heat generated by EV batteries, which can be detrimental to battery performance and lifespan. The section mainly focuses on cell cooling method and liquid/air cooling method.

Air cooling is divided into natural convection cooling and forced convection cooling. Natural convection cooling is the least complex and basic cooling method (Zhao et al. 2023). However, natural convection cooling shows a much lower heat transfer rate than forced convection cooling (Akinlabi and Solyali 2020). The liquid cooling method has higher system complexity than the air cooling method in that it requires a separate coolant and related systems other than air (Chen et al. 2016). However, liquid cooling shows a heat transfer rate that is 2 to 3 times greater than forced convection cooling (Liu et al. 2017). Currently, most electric vehicles use liquid cooling, and only a few, including Nissan, use forced convection cooling.

The cell cooling uses phase change material (PCM), heat pipes, and fins. The liquid cooling technique uses a cooling plate with micro-channels, while air cooling uses tubes with different shapes, such as straight, Z-shaped, and U-shaped. The section also mentions various optimization techniques employed for both liquid and air-based cooling methods.

2.1.1 Battery cell thermal management

During the process of converting battery energy into EV power, heat is generated, making battery cell heat control crucial for effective and safe battery operation. The temperature of a battery cell has a significant impact on its power, and excessively high temperatures can lead to thermal runaway. To manage cell temperature, various techniques are applied to battery cells, including PCM, heat pipes, and fins, among others.

The PCM approach utilizes a material's latent heat to prevent sudden temperature increases in battery cells. A material with high latent heat capacity and a phase change temperature suitable for the battery thermal management system's temperature range is selected for PCM. Since the temperature rise of the battery cell slows down while the PCM undergoes a phase transition, this method is primarily used to avoid rapid temperature increases in a short period of time.

A study conducted by Weng et al. (2019, 2020) proposed a PCM-based approach to reduce the temperature rise of cylindrical battery cells by placing the PCM in close proximity to the battery cell. The study evaluated the thermal management performance by varying the presence of PCM,

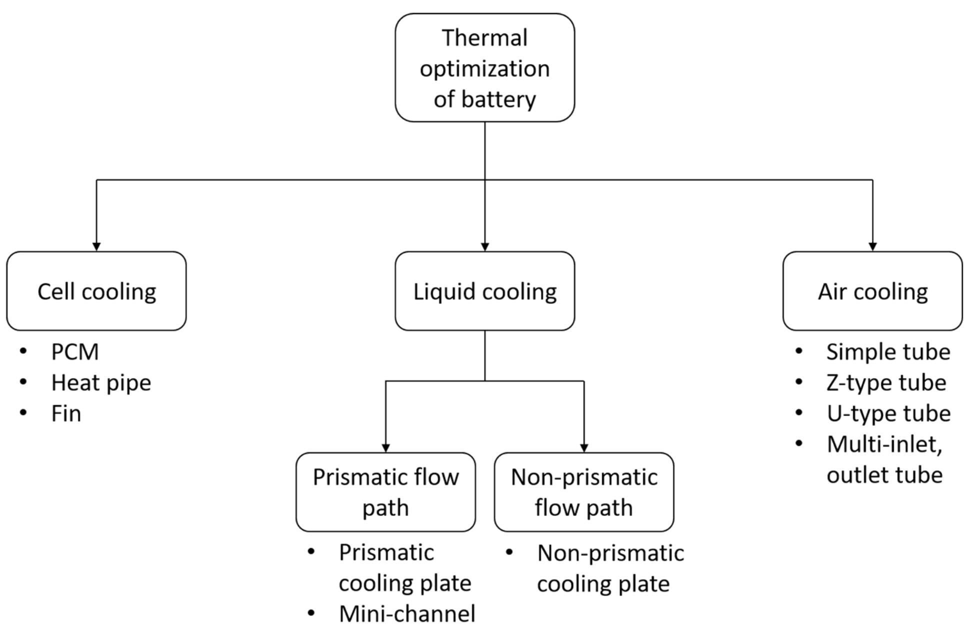


Fig. 3 Overview of thermal optimization of EV battery

its phase change temperature, and the amount of PCM used. Zhao et al. (2017) reported the results of applying PCM to a system of cylindrical battery cells, where the PCM was positioned in the middle of the cell. Li et al. (2018a) suggested a technique for reducing the mass of the cylindrical PCM by improving its geometry and filling it with multiple cylindrical battery cells. The study optimized several parameters that affect the structure of the PCM system. Javani et al. (2014) proposed an approach to maximize the mass fraction of PCM in terms of exergy, using the non-dominated sorting genetic algorithm II (NSGA-II) optimization technique. Youssef et al. (2022) suggested the use of jute fibers in conjunction with PCM for optimizing the cooling system of a battery cell, as jute fiber is an inexpensive and lightweight material with excellent cooling properties.

A battery module is a collection of multiple battery cells in an EV, and PCM can be used for cooling this type of module unit. When many prismatic battery cells are joined in a battery module, Wu et al. (2017) suggested optimizing the percentage of PCM used. In their study, a PCM module based on paraffin/expanded graphite composites was specifically used. For numerous cylindrical battery cells coupled to form a battery module, Wu et al. (2020a) recommended structural optimization of PCM.

Heat pipes are an improved technique for quick heat transfer. Behi et al. (2020a, 2020b) proposed a method of applying heat pipes to air cooling and liquid cooling. In their study, heat pipes were added to the side of cylindrical battery cells as part of an analysis of a system utilizing forced air cooling. He et al. (2022a) put forth a technique to minimize thermal contact resistance between the heat pipe and battery cells in liquid cooling. To improve the contact area and decrease thermal resistance, the heat transfer sheet was wrapped in an arc around the side of the cylindrical battery cell and the side of the heat pipe. Ye et al. (2015, 2016) proposed a method of applying a heat pipe to a prismatic battery cell.

Heat pipe cooling is commonly combined with other cooling systems for battery cell thermal management. Zeng et al. (2022) suggested system optimization using cooling plates and micro heat pipes. In this method, the heat is transferred from the battery cell to the cooling plate by the U-shaped micro heat pipe. Lei et al. (2020) proposed water spray optimization for battery cell cooling, where water is sprayed directly onto the heat pipe connected to the battery cell to remove heat. Zhang et al. (2021a) proposed the structural optimization of a combined battery cell cooling system using PCM and heat pipe. Design elements such as the length of the heat pipe, the thermal conductivity of the PCM, its thickness, and the velocity of the incoming water were taken into account in this study.

The most basic technique for quick heat transfer involves fins. The thermal impact of using pin–fin for battery air cooling was examined by Mohammadian et al. (2015). Fins are frequently combined with other cell thermal control techniques, such as PCM. Choudhari et al. (2020) suggested an improvement to battery thermal management structure using fins and PCM. In this paper, the fins are positioned parallel to the cylindrical battery cell's side, helping the PCM receive heat from the battery cell. Wang et al. (2021a) presented a cooling system for optimization that combines an L-shaped fin and a liquid cooling plate. Control of battery cell temperature is the most crucial aspect of EV optimization, and optimizing battery cell temperature is frequently done in conjunction with optimization of other aspects.

Immersion cooling is a method of cooling the battery cell by directly contacting the electrically insulated working fluid. Immersion cooling can produce about 10,000 times more heat transfer than passive air cooling (Roe et al. 2022). Roy et al. (2022) proposed a method for optimizing the flow path of immersion cooling. The shape of the flow path was optimized through topology optimization, and pressure drop and heat transfer rate were used as objective functions.

Like high temperatures, low temperatures affect the performance and safety of battery cells (Wu et al. 2020b). At low temperatures below 0 °C, the electrolyte conductivity, the charge-transfer kinetics and the solid-state diffusion of lithium ions are lowered. Accordingly, the internal resistance of the battery cell increases and the discharge capacity decreases. When charging at a low temperature, the lifespan of the battery is reduced due to problems such as anode lithium plating.

In order to solve this problem, a battery heating method has been studied in many papers. The battery heating method includes external heating method and internal heating method. The external heating method heats the battery cell through heat transfer from the outside. Ma et al. (2022) proposed a method for optimizing a battery heating system using liquid. The temperature of the battery cell and the pressure of the liquid were used as the objective function, and the genetic algorithm was used as the optimization algorithm. The internal heating method is a method of heating a battery cell using the power inside the battery. The internal heating method has the advantage of being able to increase the temperature faster than the external heating method and not being affected by the shape of the battery. Zhu et al. (2021a) proposed a method for optimizing the operation of a resonant self-heater, one of the internal heating methods. Heating speed, efficiency, and reliability were used as objective functions, and a genetic algorithm was used as an optimization algorithm.

2.1.2 Liquid cooling for battery

The primary cooling technique used to remove the last of the heat from EV batteries is liquid cooling. In liquid cooling, heat from EV battery cells is transferred to a cooling plate, which removes heat from the battery via conduction. Liquid-based micro channels are sometimes installed between the battery cells to help disperse the heat generated by the battery cells. Liquid coolant flows through a flow path inside a cooling plate, and convection is how the liquid coolant transfers heat to the final heat-removal component of the EV's radiator.

A typical cooling plate has a prismatic flow path, where the full geometry of the flow route can be described by only a few variables such as the flow channel's height and width. Various studies have demonstrated that relatively simple parametric optimization can be easily performed for the prismatic flow path. Figure 4 shows the shape of the prismatic flow path with parametric optimization applied. Jarrett et al. (2011, 2014) and Chen et al. (2019) put forth the optimization technique by parametrically designing prismatic flow patterns, improving the prismatic flow path's form parameters, using characteristics of the cooling plate such as its maximum temperature or its standard variation in temperature as the objective function.

Parametric studies were also performed on other modified simple flow path structures. These studies employ a flow path with a complex shape, but they still use a shape that can be represented by several parameters. Deng et al. (2019a, 2019b) proposed the bifurcating network flow path instead of the conventional prismatic cooling plate flow method. The classic prismatic flow path has a considerably simpler structure than the bifurcating network flow path, which has a lot more complicated structure. Deng et al. (2020) used NSGA-II to optimize the structure of a double-layered bifurcation channel. Xie et al. (2017a) suggested the optimization of a battery module's primitive cooling plate, where the performance of several prismatic cooling plate structures was evaluated. Shang et al. (2019) put forth a technique for improving the bottom cooling plate construction of a battery module made up of several prismatic battery cells, where design variables included mass flow rate, intake temperature, and cooling plate width. Tang et al. (2019) suggested an approach for improving the bottom and side cooling plate constructions of a battery module made up of several prismatic battery cells.

Numerous research studies have focused on optimizing the flow channel of liquid cooling systems for EV batteries while taking the battery's temperature distribution into account. In these studies, the objective function is typically the temperature of the battery cell rather than the cooling plate. Chen et al. (2022a) proposed an optimization method that combines the single battery cell and the cooling plate, while Wang et al. (2019a) suggested finding the optimal cooling plate shape by considering the temperature of the cylindrical battery cell.

Some liquid cooling systems use cooling plates with tiny channels, known as mini-channels, to improve battery cell heat dissipation. Li et al. (2019a) proposed an optimization approach for the prismatic flow path in the liquid-based mini-channel, while Wang et al. (2021b) presented an optimization approach for a prismatic flow path with numerous inlets and outlets in a liquid-based micro channel. An et al. (2019) proposed a technique for improving the prismatic flow path of a mini-channel cooling plate connected to a battery cell, while Monika et al. (2021) suggested a technique for improving the mini-channel flow channel of a pouch type battery cell. These studies considered design factors such as mini-channel width, channel count, cooling water type, liquid flow rate, and cooling water temperature. Zhang et al.

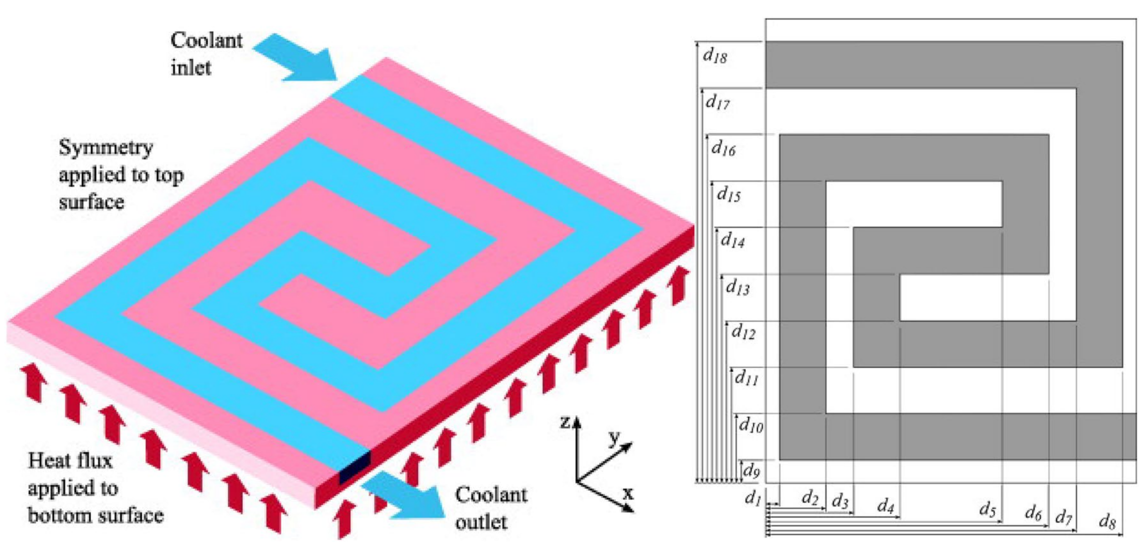


Fig. 4 Cooling plate shape optimized by parametric optimization (Jarrett and Kim 2011)

(2022a) presented a cooling plate with micro-channels that significantly improves the plate's ability to exchange heat by using interior fins in the micro-channel. Khan et al. (2022) proposed an innovative U-shaped lightweight liquid cooling technique that removes heat through the side edge of a prismatic battery cell using a U-shaped mini-channel flow path, using a machine learning approach.

In contrast to parametric optimization, topology optimization can be used to construct a variety of flow pathways, enabling the design of variable and intricate flow path. Figure 5 shows the shape of the cooling plate with topology optimization applied. Mo et al. (2021) proposed a non-prismatic flow path through topology optimization, while Guo et al. (2022) put forth a strategy for optimizing a multi-input flow channel using topology optimization.

2.1.3 Air cooling for battery

The second most popular cooling technique for removing heat from batteries is air cooling. In this method, air travels through a tube and removes heat from the battery cells, with convection occurring between the air and the battery cell. The battery cells in the simple tube method are arranged in a straight tube, which is primarily used for cooling cylindrical battery cells. Cheng et al. (2020) proposed a multi-objective genetic optimization approach for a cylindrical battery cell module, using both the average battery cell temperature and the system's pressure drop as objective functions. Fan et al. (2021) suggested a cylindrical battery cell module specifically design for high-temperature environment.

The most common tube structure used in air cooling is the Z-type tube. The Z-type tube has an inlet and an outlet that are parallel to each other and have the same air flow direction, resulting in lower pressure drop than other tube structures. Chen et al. (2017) proposed a technique for maximizing the space between battery cells in a Z-type tube. Zhang et al. (2021b) suggested modifying the shape of the spoiler and attaching it to the Z-type tube to regulate airflow and reduce the average temperature and standard deviation of the battery cells.

Another traditional method of air cooling is the use of U-shaped tubes. The U-type tube has an inlet and an outlet that are parallel to each other and have opposite air flow directions. Chen et al. (2018a) proposed a technique for improving the design of the inlet and outlet passageways in U-type tubes. Li et al. (2019b) put forth a method for simultaneously adjusting the size of the inlet and outlet channels and the separations between battery cells in a U-type tube. Liao et al. (2019) adjusted the shape parameters of the U-type tube using the maximum value and standard deviation of the battery temperature as the objective function. Additionally, experimental verification of the best designs was carried out in this research. Xie et al. (2017b) proposed a method of changing the angles of the air inlet and exit of a U-type tube and optimized these angles. Li et al. (2018b) suggested optimizing U-type tube air cooling by considering the size of the passages and the heat transfer from the battery cell to the cooling air. Wang et al. (2018, 2017a) created a multidisciplinary surrogate-based design optimization for battery air cooling, using surrogate models to simultaneously optimize the temperature differential between battery cells and battery volume.

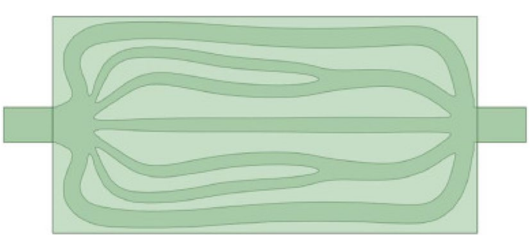


Fig. 5 Cooling plate shape optimized by topology optimization (Mo et al. 2021)

Multi-inlet, multi-outlet air cooling structures have been studied as an alternative to traditional type tubes, with various positions and numbers of inlets and outlets. Zhao et al. (2022a) and Wang et al. (2021c) compared different tube geometries with various orientations, locations, and numbers of inlets and outlets. Shi et al. (2021) suggested using deep learning to improve the design of a U-type tube with a sub exit. Liu and Zhang (2019) proposed a technique for optimizing the distance between battery cells in a J-type tube with two outlets. Zhang et al. (2021c) suggested a technique for optimizing the geometry of the outlet channel in a T-type tube with two exits. Zhang et al. (2022b, 2021d) proposed a technique for optimizing the design of multi-vent air cooling with numerous outputs. Hwang et al. (2014) proposed a technique for improving the shape of a tube with top outputs and side inlets.

Air cooling is also applied to EV components other than the batteries, and sometimes, it is possible to optimize the system when the battery and other components are both cooled by air. Widyantara et al. (2021) proposed the optimization of a system that integrates a prismatic battery cell air-cooling system and a cabin HVAC system. Table 1 is a table showing the design variables, constraints, and objective functions of the optimization problem in Sect. 2.1.

2.2 Battery charging management

While considering the battery, one of the major aspects to be optimized is the battery charge and discharge mechanism. Charging and discharging an EV or a fleet of EVs without any scheduling and optimization techniques in an uncoordinated way can be detrimental for both the battery of the EV and the power grid. In the following, we will review

Table 1 Design variables, constraints, and objective functions for optimization problem in Sect. 2.1

Section	Design variables	Constraints	Objective functions
2.1.1	Shape of heat spreader with PCM, location of heat pipes	Mass of PCM, number of heat pipes	Maximum temperature of battery cell, variance of temperature
2.1.2	Shape of flow path for cooling plate	The shape of the flow path is constrained by the size of the cooling plate	Average temperature of cooling plate, variance of temperature, pressure drop of coolant
2.1.3	Shape of air passage, arrangement of battery cells	Distance between battery cells limited by overall tube size	Maximum temperature of battery cell, variance of temperature, pressure drop of air

the literature on battery charging and wireless fast charging strategies. The electrical optimization of EV battery can be broadly classified as presented in Fig. 6.

2.2.1 Battery charging/discharging

2.2.1.1 Background to battery charging/discharging Optimizing the battery charge and discharge mechanism is crucial in managing EVs and their impact on the power grid. Uncoordinated charging and discharging can be detrimental to both the EV battery and the grid. El-Bayeh et al. (2021) categorized charging and discharging strategies into two types: uncoordinated and coordinated. Uncoordinated charging refers to the practice of charging EVs without considering the demand on the electricity grid or the availability of renewable energy sources, leading to a strain on the grid and increased energy costs. Coordinated charging strategies take into account the grid demand and renewable energy availability, optimizing electricity use and reducing grid impact. Coordinated charging involves charging EVs during times of low energy cost, high availability of renewable energy, or when excess renewable energy is available.

Some of the main reasons why optimized and coordinated charging/discharging strategies are important are listed below:

Range anxiety: One of the main concerns for EV drivers is the limited range of their vehicles in comparison to gasoline-powered cars. By carefully managing the charging and discharging of their battery, drivers can optimize the range of their EV and reduce the likelihood of running out of charge while driving.
Battery longevity: Lithium-ion batteries, which are commonly used in EVs, have a limited number of charge and discharge cycles before they start to degrade. By charging and discharging the battery at an optimal rate, drivers can extend the life of their battery and delay the need for costly replacements.
Energy cost: The cost of electricity can vary significantly depending on the time of day and the location. By charging their EV during times when electricity is less expensive (such as at night), drivers can save money on their energy costs.
Grid stability: As more and more people adopt EVs, it is important to consider the impact on the electricity grid. Charging and discharging strategies that are coordinated with the grid can help to stabilize the demand for electricity and reduce the risk of blackouts or other disruptions.

Uncoordinated charging/discharging strategies are further classified intro three sub-categories: direct, delayed,

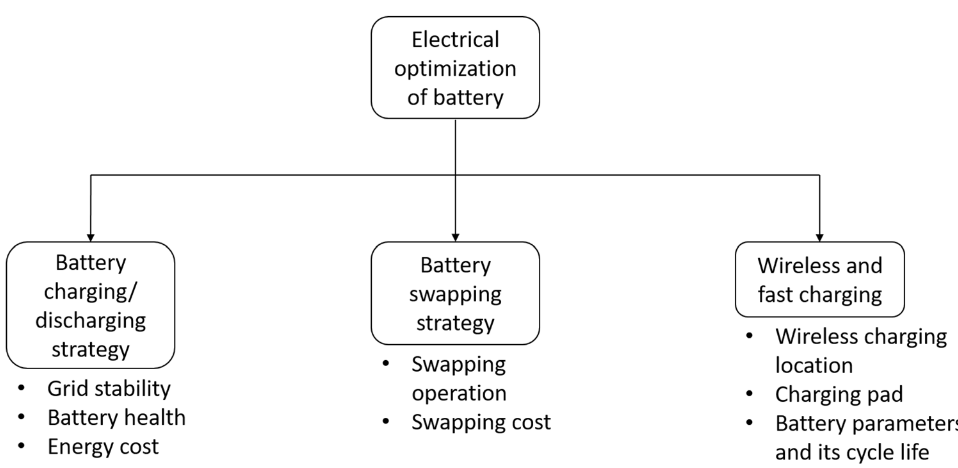


Fig. 6 Overview of electrical optimization of EV battery

and random. Direct charging means that an EV starts charging as soon as it is plugged in and stops either when it is disconnected or when the desired state of charge is reached. Delayed charging means that the charging of an EV is started during off-peak hours to help reduce the load on the power grid. Random charging is similar to direct charging, but the plug-in times of the EVs are randomly distributed.

Coordinated charging/discharging strategies can also be sub-categorized into two types: continuous and discrete, which are further classified as direct and delayed, similar to uncoordinated charging/discharging strategies. In continuous charging/discharging, an EV is charged continuously without dividing the charging/discharging time into separate intervals. This strategy is typically used at home or at a charging station. In discrete charging/discharging, the charging time of an EV is divided into separate time intervals (e.g. 15-min intervals). This strategy is typically used at charging stations. There is a lot of potential for optimization techniques to be used to find or design optimal charging/discharging strategies. Figure 7 is a table summarizing charging strategies of EV battery.

2.2.1.2 Optimization in battery charging/discharging EV charging and discharging scheduling optimization is crucial to alleviate the load on the power grid. Various studies have proposed methods to optimize the scheduling of EV charging and discharging. He et al. (2012) developed a global and local scheduling optimization problem to minimize the total cost of charging and discharging all EVs within a day. Saber and Venayagamoorthy (2009) proposed a vehicle-to-grid scheduling optimization problem using a balanced binary version of particle swarm optimization (PSO), where EVs are charged during off-peak hours and discharged during peak load hours. Coordinated charging and discharging of EVs on the grid can flatten the voltage profile and reduce power transmission loss, as demonstrated by Singh et al. (2010). Chen et al. (2018b) proposed an EV grouping method to effectively meet each group's charging demand and a coordinated optimization of EV charging and charging pile selection method to minimize the annual cost and power purchase cost. To handle the large number of EVs and their stochastic parameters, Zheng et al. (2013) proposed an aggregation charging model that uses a genetic algorithm (GA) to obtain the stochastic feature parameter, which can help reduce power fluctuation caused by EV charging. Fang et al. (2021) proposed a multi-objective comprehensive charging/discharging scheduling strategy for EVs based on improved PSO to enhance the peak regulating capacity of the power grid and reduce costs. Gu et al. (2021) proposed a decentralized discharging strategy in the vehicle-to-grid framework that uses a whale optimization algorithm, which maintains privacy by not exchanging critical information between the EV and EV aggregator.

Li et al. (2021a) developed a battery pack model to describe the state parameters and interaction of a single battery in the pack. They proposed a multi-objective optimization framework for an optimal charging strategy, targeting charging time, aging, and charging energy loss. Min et al. (2017) proposed an optimal battery charging strategy based on a multi-objective optimization framework to satisfy the EV's charging demand for charging time, charge capacity, and energy loss. Lin et al. (2019) proposed a multi-objective optimal control problem using a physics-based battery model to investigate the charging strategies that optimally trade off temperature rise, charging time, and energy loss. Zhang et al. (2017) proposed a polarization-based charging time and temperature rise optimization strategy for lithium-ion batteries, using a GA to find the optimal charging current profile. Li et al. (2020a) proposed an adaptive multistage constant current–constant voltage (MCCCV) strategy for

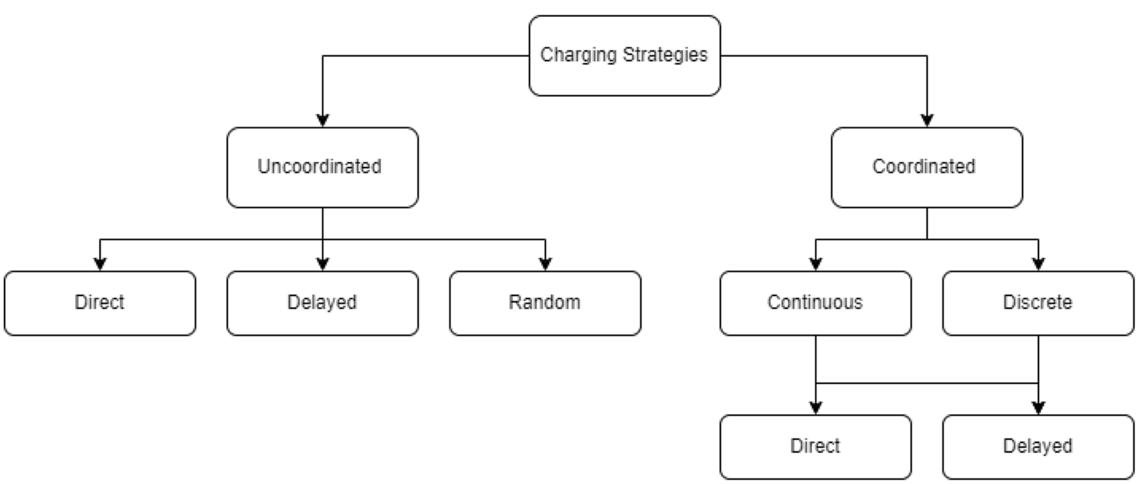


Fig. 7 Overview of charging strategies of EV battery

charging EVs and optimizing charging current using PSO. Zhang et al. (2014) analyzed the trade-off between charging loss and charging time through dynamic programming optimization algorithms. Hoke et al. (2014) proposed an optimization framework to minimize the cost of EV charging given variable electricity cost and battery degradation cost, using a simplified battery lifetime model. Du et al. (2018) proposed a multi-objective optimization framework to simultaneously optimize the heating time and energy consumption while minimizing the battery capacity degradation. Corno and Pozzato (2019) proposed a framework for battery aging management that uses a Markov chain model to model driving behavior, reducing the need for battery pack replacements and lowering maintenance costs. Wang et al. (2022a) proposed a framework that uses nonlinear model predictive control to acquire real-time charging current by solving nonlinear optimization problems. Wang et al. (2021d) proposed a dynamic programming method to minimize travel time and charging cost while determining the optimal amount of charged energy at each charging station available in the route. Chen et al. (2022b) formulated a multi-objective optimization problem for battery charging mode, taking into account energy loss and charging criteria, and achieved the optimal solution using quadratic programming. Liu et al. (2005) proposed an ant colony optimization-based method to find the optimal rapid charging pattern for batteries.

Battery diagnostics and prognostics are essential aspects of battery management systems, particularly in applications where reliable and efficient battery performance is crucial. To ensure optimal battery performance and prevent unexpected failures, it is essential to implement effective diagnostic and prognostic techniques.

Dubarry et al. (2012) describe a modified equivalent circuit model (ECM) that emulates cell performance using two independent half-cell modules built from laboratory experimental data. The model may simulate numerous "what-if" scenarios of battery deterioration modes using a synthetic approach based on specific electrode behavior, with the loading ratio and the level of degradation in and between the two electrodes properly adjusted. Weddington et al. (2021) studies the fusion of prognostic results from several methodologies in order to achieve a more reliable remaining usable life (RUL) prediction, and presents experimental results of lithium-ion batteries. The feature data is used to create models for the extended Kalman filter (EKF) and the particle filter (PF). The outputs of EKF and PF are then combined using Dempster-Shafer theory (DST). To implement multi-model prognostics and optimize performance, separate models for EKF and PF are used. Yan et al. (2017) offer an online model parameter adaptation technique, which is realized by a recursive least square method with a forgetting factor, and used a Lebesgue-sampling-based fault diagnosis and prognosis (LS-FDP). The advantage of LS-FDP is that it requires less computation and accumulates less uncertainty. The accuracy and precision of LS-FDP, like other diagnostic and prognostic techniques, are heavily influenced by the parameters and uncertainties in the diagnostic and prognostic models. Furthermore, the model noises are adjusted using a short-term prediction and correction loop to manage the uncertainty of remaining usable life (RUL) prediction.

Wang et al. (2021e) propose a novel battery health estimation framework based on an optimized multiple health indicators (MHIs) system using fuzzy comprehensive evaluation (FCE) and improved multivariate gray model (IMGM) to address the challenges of predicting and diagnosing state-of-health (SOH) of batteries due to the complicated and unobservable electrochemical reaction inside the batteries. The Box-Cox transformation method is used to extract and optimize health indicators (HIs) such as partial incremental capacity curve peak area (PICA) and partial charge time period. Thermal runaway is a significant difficulty in the Li-ion battery area due to its unpredictable and irreversible nature, which can result in fires and explosions, endangering public safety. As a result, thermal runaway prognosis and diagnosis are important study areas. Tran et al. (2022) aim to efficiently investigate current thermal runaway prognosis and diagnosis algorithms that aid in modeling, prediction, detection, and can aid in the development of prevention and mitigation measures to assure the battery system's safety.

Recent advancements in “Big Data” analytics and related statistical/computational tools raised interest in data-driven battery health estimation. Long et al. (2019) proposed an improved LSTM prediction approach for estimating lithium-ion battery RUL. Li et al. (2022) suggested a data-driven parameter identification framework for electrochemical models of lithium-ion batteries in real-world operations using artificial intelligence, specifically the cuckoo search method. Only current and voltage data are utilized as input for the multi-objective global optimization of parameters, which takes into account both voltage error between the model and the battery as well as relative capacity error between two electrodes. Bayesian approaches can be applied to a wide variety of study topics, making them one of the most appealing tools in prognostics and health management. Ouyang et al. (2023) evaluate and summarize commonly used online power battery health prognosis approaches using models and Bayesian theory. The advantages and disadvantages of the most often used empirical models, electrochemical models, equivalent circuit models, and black box models, as well as their current research status, for battery modeling were summarized. The estimate approaches based on Bayesian theory, including Gaussian filters, Monte Carlo filters, and Bayesian optimization methods, are extensively summarized for state estimation, and the merits and limitations of these methods in battery health diagnosis were discussed.

2.2.2 Optimization in battery swapping technique

Battery swapping is a technique that enables the replacement of depleted EV batteries with fully charged ones quickly and easily, thus addressing the issue of long charging times for EVs. One of the main benefits of this technique is much faster charging times compared to traditional EV charging methods. It is particularly useful for commercial fleets or ride-sharing companies, as it reduces the amount of time vehicles need to be taken out of service for charging, and for long-distance travel, as it allows drivers to swap out their batteries at strategic locations along their route. Battery swapping can potentially reduce the overall cost of owning an EV as the owner does not have to purchase a new battery and can simply pay for the cost of swapping out their depleted battery. This also extends the life of the battery, as there is no degradation of the battery over time.

Rao et al. (2015) proposed an optimization charging mode to determine the impacts of battery swapping behavior on the power grid and generation cost. Infante et al. (2019) proposed an optimal recourse strategy to coordinate the planning and operation of battery swapping stations, dealing with the stochastic parameters of the EV station. Yang et al. (2019a) proposed a shared battery station model to maximize the total revenue by controlling the charging, discharging, sleeping, and swapping of batteries. They used a GA is used to validate the optimization model. Yang et al. (2020) proposed an aggregated shared battery station model and used GA to optimize the charging, discharging, and sleeping process of the batteries to maximize the operating revenue. Sun et al. (2017) proposed an optimal charging operation problem based on a queueing network model as a constrained Markov decision process for battery swapping and charging station to minimize the charging operation cost and ensure quality service. To deal with the stochastic nonlinear dynamics of a battery swapping station operation, Wang et al. (2020a) proposed a deep Q-learning network that can perform optimal scheduling. Considering the charging demand uncertainty and electricity prices, Schneider et al. (2018) developed an algorithm based on dynamic programming and Monte Carlo sampling to minimize the operating cost of a battery swap station in a network where lateral transshipments are allowed.

2.2.3 Wireless/fast charging system

2.2.3.1 Background to wireless charging systems Currently, EVs are mostly charged through traditional plug-in methods using electric cables. However, plug-in changing systems have some disadvantages, such as the risk of sparking over plugging and unplugging the vehicle, limiting their use in certain areas like gas stations and airports. In contrast, wireless electric vehicle charging systems offer several advantages over traditional wired charging systems. For example, they allow for the convenience of charging by simply parking the EV over a charging pad, without the need to physically connect a charging cable. This makes the charging process more convenient for drivers and reduces the risk of damage to the charging ports. Additionally, wireless charging eliminates the need for drivers to handle charging cables, which can reduce the risk of electric sparks and shocks and increase safety. Since wireless charging systems do not require physical connections, they are less prone to wear and tear, improving the reliability of the charging system and reducing maintenance costs. Moreover, wireless charging systems can be installed in various locations, such as public parking garages and streets, making it easier for drivers to find charging locations. Additionally, wireless charging opens up new opportunities for dynamic charging, which is charging while driving. This eliminates the range limitations of EVs and reduces the requirement for higher battery capacity.

2.2.3.2 Optimization in wireless charging systems The need for wireless charging of EVs has led to a number of review papers in recent years. Kalwar et al. (2015) provided a review of the analysis and characteristics of inductively coupled power transfer (ICPT) for EV charging. Ahmad et al. (2017) provided a comparative study of conductive charging and wireless charging, and provided a detailed description of static, dynamic, and quasi-dynamic wireless charging systems. Panchal et al. (2018) provided a basic overview of the wireless charging system for EVs, with applications in both stationary and dynamic situations. They demonstrated different core and ferrite shapes used in wireless charging pad design. Machura et al. (2019) provided an in-depth review of various technologies and components used in wireless charging systems, and discussed environmental impacts and cost analysis in detail. Meligy et al. (2021) focused on maximizing total energy transfer while meeting budget constraints using traffic simulations and nonlinear optimization methods. The deployment optimization problem aims to determine the best locations and lengths of dynamic wireless charging lanes at each location. Ko and Jang (2013) developed a mathematical model and applied an optimization technique utilizing PSO to efficiently distribute wireless power transmitters and determine the necessary battery capacity for an online EV-based mass transportation system. Majhi et al. (2022) proposed a mixed integer optimization framework to minimize the cost for optimal placement of dynamic wireless charging facilities on a road network while maintaining a sustainable state of charge level.

Wireless charging systems for EVs use electromagnetic induction to transfer power from a charging station to the EV battery. The charging station includes a transmitter coil connected to an alternating current power source, which generates a changing magnetic field. This magnetic field is detected by a receiver coil in the EV, which is connected to the battery. The changing magnetic field in the receiver coil induces an alternating current that charges the battery. Significant research has been conducted on the design, analysis, and optimization of wireless charging systems for EVs. Hasanzadeh et al. (2012) proposed a circular coil configuration-based wireless charging system, in which the coil dimensions are optimized. An analytical model of the system is developed to find the optimal dimensions. Tan et al. (2019) proposed a dimension reduction-based fast multi-objective optimization of coil design in wireless charging systems, considering human electromagnetic safety as one of the optimization objectives of coil design. They used the NSGA-II algorithm to optimize the coil design.

2.2.3.3 Fast charging optimization The adoption of EVs heavily depends on the ability to quickly charge their lithium-ion batteries. Very high power charging infrastructure is already being implemented in numerous places through collaboration between public and commercial entities. Battery-related research is being driven by this deployment to make lithium-ion batteries accept higher charging power and significantly shorten charging times. Mathieu et al. (2021) suggested a numerical optimization of fast charging techniques and how they affect battery cycle life. They formulated an optimization problem based on a highly coupled electro-thermal model to specify the parameters of a multi-stage constant current charging technique, which can shorten charging times and/or slow down deterioration while maintaining a long cycle life. Zhao et al. (2022b) explored the kinetic factors that prevent lithium-ion batteries from charging quickly and provided a summary of research methods for improving interfaces and electrodes. Jiang et al. (2022) proposed a fast-charging Bayesian optimization approach that explicitly contains limitations that prevent degradation. They evaluated three different types of acquisition functions (expected improvement, probability of improvement, and lower confidence bound) for exploring and utilizing the parameter space of charging protocols and showed that the probability of improvement acquisition function has lower mean and best minimum charging times.

Thakur et al. (2023) thoroughly studied the battery thermal management system for fast charging application. Due to its weak heat transfer coefficient and reduced thermal conductivity, air-cooled BTMS is unsuitable for quick charging. PCMs with solid–liquid phase transitions are favored for thermal control, however secondary heat dissipation is required for longevity. Future research will focus on hybrid PCM-based BTMS, which combines liquid-based cooling plates with PCM for high heat dissipation rates. Inconsistencies in battery kinds, dimensions, capacity, and operational conditions make determining their value difficult. To build innovative battery-based systems that combine refrigerants, TE coolers, and nanofluids, more research is required. This hybrid combination provides a small unit with excellent heat dissipation and safety. Some gaps were observed, and additional research is needed to better understand how battery cells/packs/modules react to the fast-charging/discharging cycle, as well as how an adjustable BTMS can be proposed to respond to thermal load based on driving requirements.

In summary, this section covered the various charging and discharging strategies in the literature, their benefits and drawbacks, and their impact on the grid, operational cost, and battery health. The optimization constraints of charging/discharging strategies as discussed in the literature were also identified. The status of wireless charging for fast charging and associated research and challenges were discussed as well. Table 2 is a table showing the design variables, constraints, and objective functions of the optimization problem in Sect. 2.2.

2.3 Mechanical optimization of battery

Figure 8 illustrates an overview of the mechanical optimization of EV batteries. In addition to electrical and thermal stability, EV batteries also require mechanical stability to withstand loads, collisions, and vibrations. Battery packs should be lightweight, durable, resistant to vibrations, and cost-effective to address these challenges. Arora et al. (2016) described the fundamental design of packaging for EV battery packs used in EV.

Table 2 Design variables, constraints, and objective functions for optimization problem in Sect. 2.2

Section	Design variables	Constraints	Objective functions
2.2.1	Charging current, charging power and charging time slot	Battery parameters, internal temperature, charge/discharge power, grid load, SoC	Minimize operating cost, total charging time, energy loss
2.2.2	Peak load, state of battery while charging, discharging or swapping	Number of batteries in a station, battery characteristics, Grid reliability, SoC	Minimize charging cost, peak shaving, valley filling, swap cost
2.2.3	Dimensions of transmitter and receiver coils, alignment and assembly parameters, location and length of charging lanes	Battery capacity, charging duration, cell temperature, limit on battery degradation, SoC level	Maximum energy transfer, efficiency and minimize infrastructure cost and energy loses

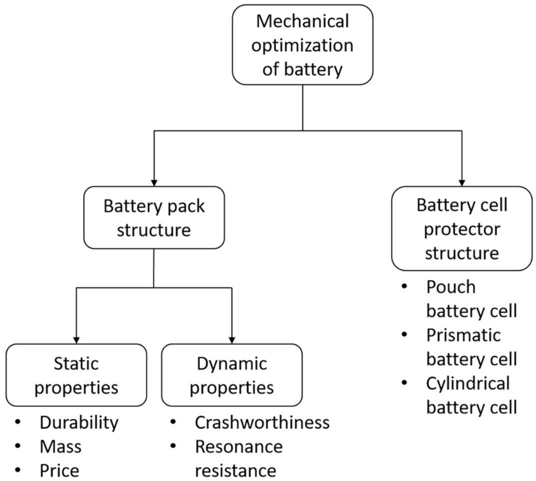


Fig. 8 Overview of mechanical optimization of EV batteries

2.3.1 Battery pack structure optimization

Research on the durability of battery packs focuses on the maximum deformation of the battery pack for a given stress. Epp et al. (2022) suggested optimizing the placement of prismatic battery cells to improve the structural integrity of the battery module. Kukreja et al. (2016) presented structural optimization for cylindrical battery cell battery packs to increase structural stability. Li et al. (2020) proposed a radial basis function neural network-based multi-objective battery pack optimization, using the battery pack's mass and maximum deformation as design variables. Xue et al. (2014) suggested a battery pack structural optimization by combining gradient-free optimization and gradient-based optimization, using the battery pack's mass, volume, and price as objective functions. Li et al. (2020b) proposed multi-objective design optimization for structural battery pack optimization, considering materials, state of health prediction, intelligent configuration, thermal design, mechanical safety, and recycling of materials and packs. Pelletier et al. (2020) suggested multi-objective optimization to improve the battery pack construction, using the battery pack's mass, maximum operating temperature, and price as objective functions. Hao et al. (2017) took driver safety, battery module structural stability, and vehicle roof strength into account in their optimization. There is also research on optimization under uncertainties. Liu et al. (2018) proposed a method to optimize the structure of the battery box under material uncertainty. The particle swarm optimization algorithm was used as an optimization method.

Instead of subjecting the EV battery pack to a fixed stress, there have been attempts to apply external forces in the form of pulses to more accurately simulate real-world crash scenarios. Qiao et al. (2021) proposed an improved structural design for the battery pact that reduces distortion in the event of a frontal collision. Zhao et al. (2013) suggested optimizing the battery pack's structure for crashworthiness while considering crash scenarios. Zhang et al. (2020a) proposed optimizing the battery pack's structure with crashworthiness in mind using multi-load topology optimization. Li et al. (2018c) suggested using resilient design optimization to optimize the battery pack's structure and demonstrated that adaptive significance sampling is more effective than simple Monte Carlo sampling for battery pack design. Zhang et al. (2019) proposed using NSGA II to optimize the battery pack's structure for crashworthiness, with the maximal equivalent stress and resonance frequency of the battery pack serving as the objective function.

Some studies aim to use the natural frequency of the battery pack as the objective function, which enables the optimization of the vibration resistance of the battery pack. These studies typically aim to maximize the minimum natural frequency. Liu et al. (Liu et al. 2022) proposed a multi-objective structural optimization approach for battery pack structural stability, with the objective function being the battery pack's stress and resonance reactivity. Lin et al. (Lin et al. 2016) proposed a multi-objective PSO method for optimizing the structural design of battery packs, with the objective functions including the battery pack's mass and the restraint of the fundamental frequency. Shui et al. (2018) suggested the used of the NSGA II method for optimizing the battery pack structure, with the objective functions being the battery pack's mass, lowest natural frequency, and maximum deformation. Niu et al. (2019) proposed optimizing the battery pack structure to improve linked electrochemical-mechanical performance, with the objective functions being the maximum deformation, the lowest intrinsic frequency, and the battery pack's mass. Pal et al. (2020) suggested using the cold spray technique to optimize the battery pack structure, with the objective functions being the maximum deformation and the lowest natural frequency of the battery pack.

2.3.2 Battery cell protector optimization

Research has also been conducted on protecting battery cells from external influences. These studies focus on strengthening the protector that shields battery cells. Biharta et al. (2022) proposed optimizing the design of a double-U structure protector to protect pouch battery cells from ground impact loads. Carakapurwa et al. (2022) suggested optimizing the protector shape of an auxetic structure used to protect battery cells using machine learning. Huang et al. (2021) proposed optimizing an X-shaped pattern protector to protect cylindrical battery cells, and Nasrullah et al. (2021) employed a cellular twisted-octet lattice structure protector for structural optimization of battery cell protectors. Shuai et al. (2020) proposed optimizing the honeycomb design of a battery pack made up of cylindrical battery cells.

Overall, various types of protectors have been studied for the mechanical stability of battery cells. Table 3 is a table showing the design variables, constraints, and objective functions of the optimization problem in Sect. 2.3.

2.4 Summary

In summary, Sect. 2.1 covered various thermal management strategies. Thermal optimization is crucial for safe and efficient operation, requiring the management of heat generated during energy conversion. Various techniques are used to regulate battery cell temperature, such as PCM, heat pipes, liquid cooling, and air cooling. Parametric optimization, topology optimization, and multidisciplinary design optimization are among the optimization techniques used for these methods.

Section 2.2 covered the various charging and discharging strategies in the literature to optimize battery performance, extend battery life, and ensure safe and efficient operation. Strategies such as constant current, constant voltage, fast charging, load shifting and peak shaving among others along with the different optimization techniques of charging/discharging strategies as discussed in the literature were also identified. The benefits and drawbacks of these strategies depends on the specific application requirements, battery chemistry, and trade-offs between charging speed, energy efficiency, and battery health considerations. Well-coordinated charging strategies offer controlled charging, cell balancing, reduced charging time along with grid stability. Impact on the operational cost was also discussed.

Optimization in battery swapping techniques were discussed which focuses on enhancing the efficiency, cost-effectiveness, and user experience of the swapping process. Strategies to locate swapping stations, optimize charging and discharging rates, select suitable batteries, manage queues, estimate battery health, integrate with the grid, and ensure system reliability were discussed from the literature.

Optimization in wireless and fast charging strategies enhance charging efficiency, alignment, dynamic power control, foreign object detection, dynamic current and voltage control, temperature management were also discussed from the literature.

Section 2.3 covered various mechanical optimization technique. Mechanical optimization ensures battery packs are lightweight, collision-resistant, vibration-tolerant, and cost-effective. Resilient design optimization, structural optimization, and protector optimization are among the optimization techniques used to improve the mechanical stability of battery modules and packs.

3 Optimization of other components in EV

While battery-related aspects are the most researched in EVs, other components such as powertrain and motors, among others, also require changes and customization. This section discusses literature focused on the optimization of such components. An overview of the optimization of main components in EVs is depicted in Fig. 9.

3.1 Powertrain

The optimization of powertrain design is crucial for achieving energy efficiency and emission reduction in EVs. Figure 10 shows the powertrain architecture of an EV. Powertrain design optimization studies include three main areas: (i) powertrain configuration optimization to determine the best powertrain topology or architecture, (ii) powertrain parameter optimization to determine the size and types of components, and (iii) control system optimization to optimize the control algorithm and energy management system.

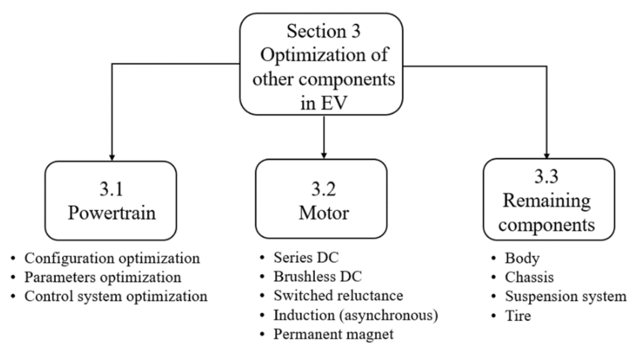


Fig. 9 Overview of optimization of other components in EV

Table 3 Design variables, constraints, and objective functions for optimization problem in Sect. 2.3

Section	Design variables	Constraints	Objective functions
2.3.1	Shape of battery pack	Input stress for battery pack, magnitude of the external force	Maximum deformation, mass, volume, price, crashworthiness and resonance resistance of battery pack
2.3.2	Shape of battery cell protector, patterns for cell protector	Input stress for cell protector, magnitude of the external force	Mechanical stability of battery cells, strength of cell protector

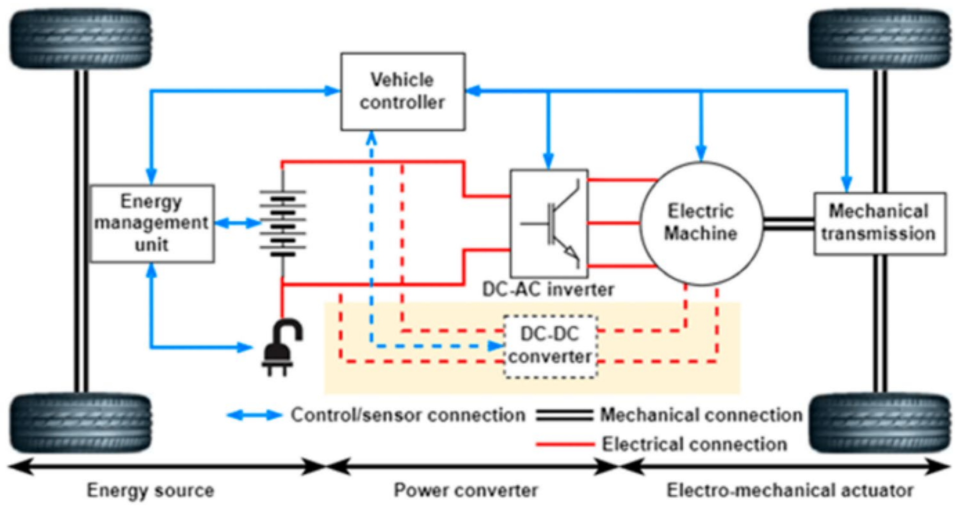


Fig. 10 Powertrain architecture for an EV

3.1.1 Powertrain configuration optimization

Powertrain architecture has a significant impact on fuel efficiency. Bayrak et al. (Bayrak et al. 2014) proposed a mathematical algorithm to automatically generate all possible topologies for a fixed set of powertrain components. However, the proposed method resulted in a large number of possible topologies, requiring substantial computational power. Various methods have been proposed to overcome this issue. For instance, Silvas et al. (2015) proposed a cost-based framework to identify feasible topologies by analyzing all possible topologies for a given set of fixed components. The resulting design space was reduced using a constraint logic program based on functionality and cost principles.

3.1.2 Powertrain parameter optimization

Powertrain parameter optimization involves optimizing various parameters such as the size and types of the components, transmission ratios, and drive motor parameters, to enhance the EV in terms of cost, fuel consumption, performance, and emissions. Parameters optimization studies can be classified into two broad categories: single-objective and multi-objective. In single-objective studies, researchers such as Wang et al. (2017b) and Coronado (2018) optimized for powertrain efficiency, Dong et al. (2018) for driving cycle range, Borthakur and Subramanian (2019) for fuel consumption, and Zhou et al. (2022a) for energy consumption. In multi-objective studies, researchers such as Wang and Sun (2014) and Wang et al. (2020b) optimized for driving range and the time required to accelerate the vehicle from 0 to 100 km/h, while Mozaffari et al. (2016) optimized for total traveling cost and the time required to accelerate the vehicle from 0 to 100 km/h. Wang et al. (2019b) used the electric energy consumption under the charge depleting stage, the fuel consumption under the sustaining stage, and the time required to accelerate the vehicle from o to 120 km/h as their objective functions. Other studies, such as those by Zhang et al. (2020b), Li et al. (2020c), Helbing et al. (2021), Chen et al. (2022c), da Silva et al. (2022), Eckert et al. (2022), Lee and Shim (2022), Nguyen et al. (2022), and Zhou et al. (2022a, b), used different combinations of parameters such as fuel economy, system durability, power cost, low speed rotor torque, driving autonomy, battery life span, storage system energy, hydrogen consumption, system cost, and performance degradation, as their objective functions to be optimized.

3.1.3 Powertrain control system optimization

In powertrain control system optimization studies, the goal is to attain optimal energy management by implementing a control strategy that regulates the operation of the powertrain of EV. The control strategy is usually implemented in the vehicle central controller and adjusts parameters such as torque and speed to meet the driver's demand for traction power while sustaining the battery charge and optimizing drivetrain efficiency, fuel consumption, and emissions. Energy management (control) strategies for EVs can be classified into three categories: rule-based, optimization-based, and learning-based, as presented in Fig. 11, a modified version of the classification given in Salmasi (2007). The representation, generation, and optimization methodology of hybrid EV powertrain architectures were discussed in Zhou et al. (2020), and a comprehensive overview of the generation, screening, and optimization of powertrain configurations for power-split hybrid EVs can be found in Zhao et al. (2021).

Rule-based control strategies use heuristics, intuition, human expertise or mathematical models to provide real-time supervisory control of the powertrain. Al-aawar et al. (2014) used adaptive neural fuzzy inference system, Lawler

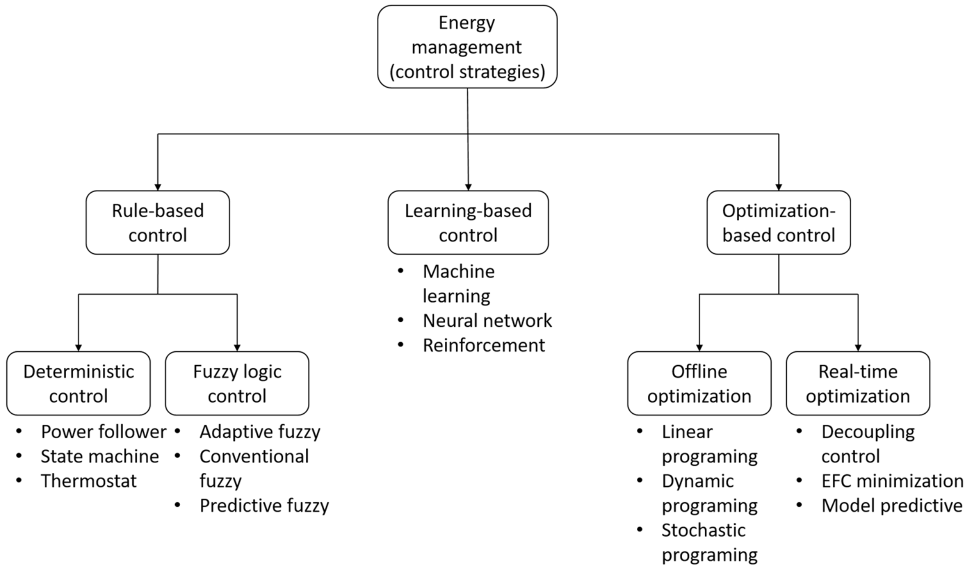


Fig. 11 Classification of powertrain energy management strategies for electric vehicles

et al. (2011) used a rule-based supervisory control, Miranda et al. (2022) used conventional fuzzy logic control for energy management of EVs.

Optimization-based control strategies aim to minimize a cost function, usually representing fuel consumption or emissions. Ahn et al. (2008) used both equivalent fuel consumption (EFC) minimization and dynamic programming, Yamamoto et al. (2020) used EFC minimization, Kargar et al. (2022) used approximate dynamic programming to generate an energy management strategy for EVs.

Learning-based control strategies use experimental sensory data to develop learners, such as neural network, to regulate the powertrain's operation. Liessner et al. (2019) used deep reinforcement learning (DRL) to optimize controls for real stochastic vehicle use, and Bayesian optimization that sequentially operates with the DRL was performed to select suitable hardware configurations. Zhou et al. (2022a, b) and Tang et al. (2022) used deep deterministic policy gradient strategy for powertrain energy management for HEVs. Du et al. (2022) developed a novel DRL control framework for the energy management strategy of the series hybrid electric tracked vehicle (SHETV). Wang et al. (2022b) proposed a DRL-based energy management system for hybrid electric vehicle integrated with waste heat recovery system (organic Rankine cycle). Zhou et al. (2022c) constructed the vehicle power model of HEV and Markov probability transfer model, and then designed the energy control strategy based on reinforcement learning, and finally compared it with the energy control strategy based on proportional integral derivative. Yan et al. (2023) addressed the energy optimization control issue for hybrid electric vehicles using three different algorithms, namely Q-learning, deep Q network (DQN), and deep deterministic policy gradient (DDPG) algorithms, and found the superiority of the DDPG algorithm over Q-learning and DQN algorithms in hybrid electric vehicles. B. A review of reinforcement learning based energy management systems for electrified powertrains can be found in Ganesh and Xu (2022).

3.2 Motor

The commonly used types of electric motors used in EVs include (1) series DC motors, (2) brushless DC motors, (3) switched reluctance motors, (4) induction motors (asynchronous motors), and (5) permanent magnet synchronous motors. The series DC motor was the most widely used motor for traction application in the early 1900s due to its high starting torque, but it is not commonly used in recent applications. Brushless DC motors were also used as traction motors in early applications due to their various advantages, such as their basic topology, wide speed range, light weight, and noise-free operation. However, this motor type is also not commonly used in recent applications. Table 4 is a table summarizing the advantages and disadvantages of various types of electric motors. Table 5 is a table showing the types of EVs in the market from 2010 to 2020 and the type and power of the motors used.

Motor diagnostics and prognostics are crucial aspects of condition monitoring and maintenance practices for various machines and equipment that incorporate motors. Motor diagnostics refers to the process of monitoring and analyzing the operational data of a motor to identify its current state and detect any abnormalities or faults. Various methods can be employed for motor diagnostics, including vibration analysis, current analysis, temperature monitoring, acoustic analysis, oil analysis and infrared thermography. Motor prognostics goes beyond diagnostics and involves predicting the future behavior and remaining useful life of a motor

Table 4 Advantages and disadvantages of electric motors

Motor type	Advantages	Disadvantages
Series DC motors	High starting torque, basic topology, wide speed range, light weight, and noise-free operation	Speed control challenge, low efficiency, requirement of frequent maintenance
Brushless DC motors	Low maintenance cost, long lifespan, high power density, high torque density, smooth operation at high speeds	High cost, low torque at high RPM, vibrations at low speeds, complex wiring, complex control
Switched reluctance (SR) motors	Smaller energy consumption, simple construction, high efficiency, robustness, high torque density	Complex control, high levels of acoustic noise and vibration, torque ripple, high manufacturing cost, low power factor, limited speed range, high manufacturing cost
Induction motors (asynchronous motors)	High starting torque, ability to brake at very low speeds, cheaper cost, less maintenance requirement, high durability	Low power factor at low loads, complex control, requires some auxiliary for stating
Permanent magnet (PM) synchronous motors	High efficiency, high power density, precise speed control, high starting torque, regenerative braking, reduced maintenance, low torque ripple	High initial cost, limited high-temperature operation, demagnetization risk, complex control

Table 5 Example of EVs on the market from 2010 to 2020

EV model	Power(kW)	Motor	Year
Mahindra e2o Plus	19–30	1M	2016
Renault Kangoo ZE	44	PMSM	2011
Mitsubishi I-MiEV	47	PM	2010
Volkswagen E-up	60	PMSM	2019
Renault Zoe	65	PMSM	2012
LandRover	70	SRM	2013
Renault Fluence			
Z.E.	70	PMSM	2012
Nissan Leaf	80	PMSM	2010
BJEV EC5	80	PMSM	2019
Hyundai Ioniq			
Electric	88	PMSM	2016
Hyundai Kona	80-150	PMSM	2018
BYD E6	90	PMSM	2014
BMW i3	125	PMSM	2013
Xpeng G3	139	PMSM	2018
Mercedes-Benz			
EQC	150*2	IM	2019
BJEV EU5	160	PMSM	2018
Tesla Model X	193-375	IM	2015
Tesla Model 3	211-340	PMSM	2020
Tesla Model S	235-568	IM	2012
NIO EC6	320	PMSM	2020
NIO ES6	320	PMSM	2020

based on its current condition and performance data. Common approaches for motor prognostics include: statistical analysis, machine learning algorithms, physics-based models, and prognostic health management systems.

Various condition monitoring solutions for electric motors have been implemented, including anomaly detection and diagnostics solutions such as vibration and stator current based fault detection (Liang et al. 2018), stator current based electro-magnetic simulation model for winding insulation diagnostics (Liu et al. 2019), rotating noise based stator and bearing fault diagnostics (Nakamura et al. 2021), or vibration and acoustic emission data based Bayesian network solution for PM synchronous motor fault diagnostics (Cai et al. 2021).

Prognostics solutions that have been presented include: digital twin and prognostics framework based on artificial neural networks (ANN) and fuzzy logic for PM synchronous motor operated in electric vehicles (Venkatesan et al. 2019), and the two-stage prognostics framework which connects Bayesian networks and autoregressive moving average models to improve the prognostics prediction accuracy (Cai et al. 2022). Generally, SVM, ANN and deep learning performs well in multi-dimensional and continuous data and k-NN, decision trees and Naive Bayes works well for discrete data (Kotsiantis et al. 2006). Current diagnostic systems are dependent on feature selection, feature extraction, data collection and so many processes, and deep learning has the potential to develop a complete diagnostic system and needs more attention.

3.2.1 Switched reluctance (SR) motors

In a couple of recent studies, SR motors have been used as traction motors because of their smaller energy consumption compared to other motor types. Sun et al. (2021) conducted multi-physics design optimization of an SR motor for an EV application. The geometric parameters of the motor were optimized for minimum stator and coil temperatures, maximum output torque, minimum torque ripple, and minimum total loss. Patel et al. (2021) performed design and optimization of a slotted stator SR motor for EV applications. They modified the conventional design by slotting the stator tooth with different depths from the inner periphery, and the geometry of the modified motor was optimized for maximum torque output.

3.2.2 Induction motors (IM)

The three-phase IM is a better option compared to the previously mentioned motor types as a traction motor due to its high starting torque under various loads and its ability to brake at very low speeds. Zhang et al. (1996) optimized an EV induction motor using sequential unconstrained minimization technique. The core axial length, winding conductor diameter, coil conductor diameter, end ring width and height were optimized for minimum motor active material length. Faiz and Sharifian (2006) optimized a squirrel-cage three-phase IM for an EV application. The number of poles, rated base speed and slot shapes were optimized for maximum efficiency. Demir and Aküner (2018) optimized an in-wheel IM for an EV application. Various motor parameters including the number of poles, input voltage, frequency, stator inner and outer diameters, engine length, numbers of stator grooves, conductors and wire cores, wire and shaft diameter, ring height and width were optimized for maximum efficiency and maximum output torque. Akhtar and Behera (2019) designed a squirrel cage IM for application in an EV. The stator and rotor slot dimensions were optimized for maximum efficiency, maximum breakdown torque, and maximum power factor.

3.2.3 Permanent magnet (PM) synchronous motors

Finally, the PM motor is currently the most attractive option as a traction motor because of its wide speed interval, high maximum accessible power, and high efficiency. Depending on how magnets are attached to the rotor and the design of the rotor, the PM motor can be classified into two types: surface-mounted permanent magnet (SPM) motor and interior permanent magnet (IPM) motor. SPM motor mounts all magnet pieces on the surface, and IPM motor places magnets inside the rotor. Sun et al. (2019) performed the design optimization of an SPM motor with concentrated windings for EV applications. Various parameters, including slot-pole number combination, machine inductance, axial length, and number of turns, were optimized to minimize the total energy losses over the driving cycle. Ahn et al. (2014) designed an IPM motor as part of a battery EV propulsion system. The motor armature coil turns, stack length, operation DC voltage, and final drive ratio were optimized for minimum charge depletion and minimum acceleration time from 0 to 60 mi/h. Hawkins et al. (2014) optimized the IPM electric motor of the General Motors 1ET35 drive unit used in the 2014 Chevrolet Spark EV. Geometric parameters, such as the shape and placement of the magnet barriers, air slots in rotors, and rotor outer surface profile, were optimized for maximum efficiency and minimum torque ripple. There are also studies that compare different types of PM motors. Sarigiannidis et al. (2016) considered both surface-mounted and interior type PM motors and optimized both types of motors. The geometric parameters (e.g., PM width and angle, stator tooth width and length, air-gap diameter) were optimized to minimize a cost function that includes the mean produced electromagnetic torque, motor power loss, total harmonic distortion, and torque ripple.

Torque generation capability and vibration characteristics are also important measures for motor optimization. Ma et al. (2018) performed design and optimization of an IPM motor to improve its flux weakening capability and reduce vibration. The PM total width per pole, the width of ducts, the pole embrace, distance from duct bottom to the shaft surface, and the minimum distance between side magnets were optimized for the minimum value of torque ripple to the average torque. Gu et al. (2019) optimized an axial flux SPM motor for an EV application. They optimized the rated torque and speed, number of poles and phases, rated voltage, and number of stator segments for maximum torque density and maximum torque ripple. Sun et al. (2019) performed design optimization of an SPM synchronous motor for a campus patrol EV. The PM structure, air-gap length and stator core geometry were optimized for maximum output torque, minimum cogging torque, and minimum PM eddy loss. Bhagubai et al. (2020) optimized a spoke-type IPM motor to be used in a Formula Student electric car. They optimized the geometric parameters, such as the rotor radius, shaft radius, permanent magnet width and length, stator tooth width and length, outer ring width, and air-gap size, for maximum efficiency and maximum output torque. You (2020) performed shape optimization of an IPM synchronous motor for an EV application. The angle between the V-shaped permanent magnets and the rib thickness of the rotor were optimized for maximum average torque and minimum total harmonic distortion of the back electromotive force. Lee and Lim (2021) optimized an IPM motor for an EV application. The geometric parameters of the motor, such as stator inner and outer diameters, air-gap and stack lengths, as well as other parameters such as the number of poles and PM remanence, were optimized for maximum torque density, maximum efficiency, and minimum torque ripple.

Efficiency and temperature rise were also among the important considerations in design optimization. Wu et al. (2021) optimized an IPM synchronous motor based on road condition of the EV. The geometric parameters including outer diameter, motor length, magnet thickness and width, and air-gap length were optimized for maximum efficiency and minimum weight. Zhu et al. (2021b) performed cooling system design optimization of a high-power density IPM traction motor for EV applications. The cooling structural parameters were optimized to reduce the steady-state temperature rise of the motor. Zhu et al. (2022) optimized the NVH (noise, vibration, and harshness) performance of an IPM motor for an EV application. Geometric parameters such as slot depth and width, and the angle between two slots were optimized to minimize the three orders of electromagnetic force. A summary of design optimization studies on PM synchronous motors for EV applications is presented in Table 6.

In addition to motor design optimization, optimal control strategies have also been implemented to improve the operation of EV motors. Zhao et al. (2018) proposed a sliding mode vector control system for collaborative optimization of an axial flux PM synchronous motor for an EV. He et al. (2022b) proposed an energy recovery strategy based on braking safety and efficient recovery to increase the energy recovery rate and reduce braking distance. They also proposed a torque optimization strategy to minimize the energy loss of the regenerative braking system and improve energy recovery during motor braking. Mehbodniya et al. (2022) optimized the energy efficiency of a three-phase induction motor using field-oriented control and direct torque control approaches. Zhai et al. (2022) developed an optimized control algorithm for the brushless DC motors of an EV.

3.3 Remaining components

The studies on EV design optimization have mostly focused on batteries, battery management systems, drivetrains and

Table 6 Design optimization studies on permanent magnet synchronous motors for EV applications

Study	PM type	Design variables	Objective functions
Sun et al. (2021)	Surface-mounted	Slot-pole number combination, machine inductance, axial length, and number of turns	* Minimum total energy loss over the driving cycle
Ahn et al. (2014)	Interior	The motor armature coil turns, stack length, operation DC voltage and final drive ratio	* Minimum charge depletion * Minimum acceleration time from 0 to 60 mi/h
Hawkins et al. (2014)	Interior	The shape and placement of the magnet barriers, air slots in rotors, rotor outer surface profile	* Maximum efficiency * Minimum torque ripple
Sarigiannidis et al. (2016)	Compared surface-mounted and interior	PM width and angle, stator tooth width and length, air-gap diameter	* Minimum cost function that includes the mean produced electromagnetic torque, motor power loss, total harmonic distortion and torque ripple
Ma et al. (2018)	Interior	PM total width per pole, the width of ducts, the pole embrace, distance from duct bottom to the shaft surface and the minimum distance between side magnets	* Minimum value of the torque ripple to the average torque
Gu et al. (2019)	Surface-mounted	The rated torque and speed, number of poles and phases, rated voltage and number of stator segments	* Maximum torque density * Maximum torque ripple
Bhagubai et al. (2020)	Interior	The rotor radius, shaft radius, the permanent magnet width and length, and the stator tooth width and length, outer ring width and air-gap size	* Maximum efficiency * Maximum output torque
You (2020)	Interior	The angle between the V-shaped permanent magnets and the rib thickness of the rotor	* Maximum average torque * Minimum total harmonic distortion of the back electromotive force
Lee and Lim (2021)	Interior	Stator inner and outer diameters, air-gap and stack lengths, the number of poles and PM remanence	* Maximum torque density * Maximum efficiency * Minimum torque ripple
Wu et al. (2021)	Interior	The outer diameter, the motor length, magnet thickness and width and air-gap length	* Maximum efficiency * Minimum weight
Zhu et al. (2021b)	Interior	The cooling structural parameters	* Minimum steady-state temperature rise of the motor
Zhu et al. (2022)	Interior	The slot depth and width, the angle between two slots	* Minimum orders of electromagnetic force

motors. However, there have also been design and optimization studies on other components such as the body, chassis, suspension system, and tires.

3.3.1 Body and chassis

Liu et al. (2013) performed a lightweight design of a carbon twill weave fabric composite body structure of an EV. They found that using the carbon twill weave fabric composite could achieve a 28% weight reduction in the body compared to its predecessor made of glass fiber reinforced plastics. Gao et al. (2018) performed a multi-objective reliability-based optimization of the front body of an EV, where uncertainties in the geometric parameters of the front body components were taken into account. The thicknesses of nine components on the front body were optimized for maximum energy absorption and minimum peak crash force under full frontal impact, with constraints on mass and natural frequency. Li et al. (2019c) performed a lightweight and crashworthiness design of EVs using a six-sigma robust design optimization approach. They optimized the material and thickness of various components, including front longitudinal and anti-collusion beams, sub-frame front, rear and anti-collision beams, and the crash box, for minimum weight and minimum peak acceleration at the left rocker in the B-pillar under frontal impact. Li et al. (2021b) performed a multi-objective optimization design of the B-pillar and rocker subsystems of an EV to improve its side crash performance. The material and thickness of the reinforcing panel and inner panel of the B-pillar, as well as the material and thickness of the inner panel and outer panel of the rocker, were optimized for minimum structural mass and maximum mean crash force. Chen et al. (2022d) optimized the body frame structure of an EV using a multi-load case multi-objective topology optimization approach based on the body structure performance, considering the battery layout and its mass distribution. The equivalent static load method was used to integrate the crash load case into the optimization framework.

Wang and Wang (2021) performed a crashworthiness-based multi-objective integrated optimization of an EV chassis frame. The thickness and shape variables of the chassis frame were optimized for minimum weight, maximum dynamic stiffness, and minimum acceleration of the battery compartment. Zhang et al. (2021e) used the equivalent static load method to perform multi-load topology optimization on the body-in-white of the EV. They found that, compared to traditional single-load topology optimization, the multi-load topology optimization could make the optimization scheme more targeted while taking full consideration of vehicle body performance. Roper and Kim (2022) used a component-existence approach to perform integrated topology and packaging optimization for an EV at the conceptual level. They compared the performance of the integrated topology and packaging optimization results to those of the equivalent topology-only problems and found that the compliance difference was less than 10% despite the addition of various complex integration requirements such as multiple geometries and packaging symmetry.

3.3.2 Suspension system and tire

Hsu et al. (2010) optimized the dynamic properties of the MacPherson front suspension and leaf spring rear suspension of an EV. They first obtained the dynamic properties of a vehicle with a gasoline engine and used them as baseline values. The diameter of the front stabilizer bar, the stiffness of the coil spring, and the thickness of the rear leaf spring were optimized for the minimum change of the lateral acceleration, roll angle, and yaw rate of the vehicle between baseline vehicle and EV. Li et al. (2019d) performed a multi-objective optimization of the active suspension of an EV to solve the negative vibration issues emerging from in-wheel-motor in EVs. The stiffness and damping in the suspension system, as well as the weight matrices in the liner quadratic Gaussian controller, were optimized to minimize the unbalanced electromagnetic excitation and vibration.

Feng et al. (2020) used the highway safety research institute tire model and developed two methods for estimating the road tire friction coefficient of a four-wheel drive EV using a moving optimal estimation strategy. Huang et al. (2022) performed uncertainty-based optimization of the tire/road structure-borne (TRS) noise of a pure EV using the interval analysis method. The pressures of the front and rear tires, the stiffness values of the subframe-body bushing, control arm bushing, and suspension spring for the front and rear systems, and the damping values of the front and rear shock absorbers were optimized. These design variables were taken as uncertain. The sound quality annoyance of TRS noise was considered the optimization objective, while the riding comfort was taken as the constraint condition. Wang et al. (2020c) designed a new particle filter to realize online identification of an unknown tire model. They considered the uncertainties in the tire model and road surface disturbances and performed optimal coordinated control combining active rear-wheel steering and direct yaw moment control.

3.4 Summary

Section 3 covers research on optimized design for other main components of EVs, including powertrain, motor, body, chassis, suspension system, and tires. Powertrain design optimization includes powertrain configuration optimization, powertrain parameter optimization, and control system optimization. In the existing studies, configuration optimization, parameter optimization, and control system optimization are performed separately, therefore sub-optimal designs are high likely obtained. Future research should focus on simultaneous optimization of configuration along with size and control parameters exploration to address the issue.

Common types of electric motors used in EVs include series DC motors, brushless DC motors, switched reluctance motors, induction motors (or asynchronous motors), and permanent magnet synchronous motors, with permanent magnet motors being the most widely used due to their wide speed range, high power, and high efficiency. The drawbacks of permanent magnet motors include high-cost magnet material and diminishing the effect of stator and rotor material losses on the efficiency and fault tolerance. Future research should focus on minimization of stator and rotor material losses to optimize the efficiency and reliability of permanent magnet motors.

Optimization research have also been conducted on other areas such as body, chassis, suspension system, and tires. Body and chassis optimization studies comprise material, thickness, and shape optimization, and recent studies focus on multi-objective reliability-based design optimization under dynamic loading. Suspension system and tire design studies focus on optimizing the dynamic properties of the suspension system, and recent studies focus on uncertainty-based optimization. Future research is expected to leverage artificial intelligence and machine learning techniques on design optimization of these components. Table 7 is a table showing the design variables, constraints, and objective functions of the optimization problem in Sect. 3.

4 EV management optimization

In the context of EV development and deployment, apart from the components that are part of the vehicle, such as suspension, Battery, motors, etc. the charging ecosystem also influences the performance to an extent that the management options reflect in government EV policy decisions. An

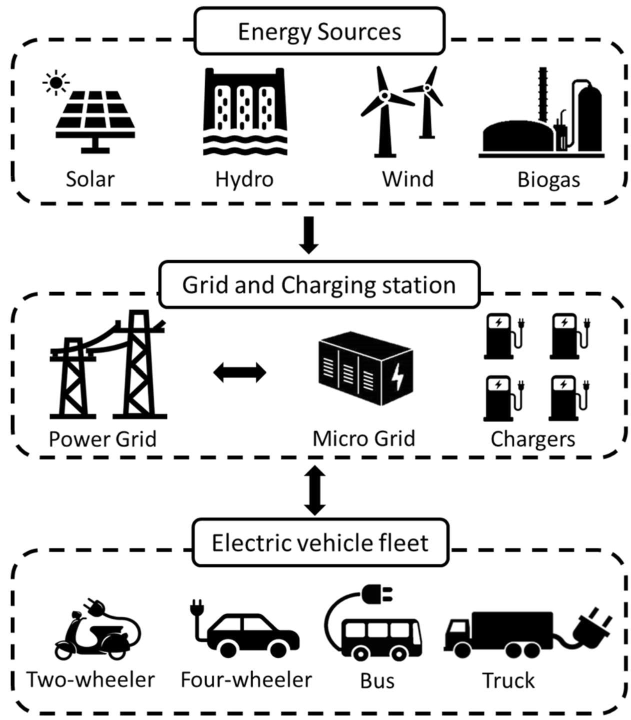


Fig. 12 Stakeholders in EV management

Table 7 Design variables, constraints, and objective functions for optimization problem in Sect. 3

Section	Design variables	Constraints	Objective functions
3.1.1	Powertrain architecture variables, driving modes	Number of clutches, packaging feasibility, battery state of charge	Fuel consumption
3.1.2	Size and types of the components, vehicle weight, transmission ratios, drive motor parameters	Vehicle maximum speed, climbing capability, acceleration time, driving range, gradeability	Total cost, fuel consumption, performance, driving range, acceleration time, battery lifespan, performance degradation, system durability, required torque
3.1.3	Engine torque, engine speed	Required power, comfort level	Drivetrain efficiency, fuel consumption, emission
3.2	Motor geometry, number of poles, rated torque and speed	Coil temperature, output torque, allowable current density, power factor, rotor speed, temperature rise	Stator and coil temperature, output torque, motor power loss, torque ripple, efficiency, acceleration time, torque density, motor weight and volume
3.3.1	Material, thickness and shape of body components,	Natural frequency, dynamic stiffness, packaging symmetry	Energy consumption, specific energy absorption, peak crush force, weight, peak acceleration
3.3.2	Stiffness and damping in the suspension system, pressure of tires	Driving comfort, road handling, stability	Energy consumption, tire/road structure-borne noise, weight

overview of the stakeholders in EV management is provided in Fig. 12. It shows the energy flow from the renewable energy sources and power exchange between power grid, charging station and EV fleet. Interoperability of these entities is essential for an optimal EV management framework.

In this section, we review the literature on the optimization of management techniques such as charging station management which includes optimal infrastructural decisions, grid management takes care of the grid instability arising from multiple power sources and fleet management which includes optimal scheduling, dispatch and autonomous fleet management. The electric vehicle charging ecosystem management is presented in Fig. 13.

4.1 EV charging station

4.1.1 Charging station management and optimization

Charging station management involves the efficient operation of charging stations and the strategies that help to maximize the use of charging infrastructure to meet the growing demand for EV. Effective management of charging stations is necessary to ensure that consumers and fleets are able to charge their vehicles efficiently. This involves designing charging stations that can accommodate different types of EVs and charging speeds, and equipping them with intelligent charging infrastructure that can monitor charging activity, manage power distribution, and optimize charging schedules.

Rogge et al. (2018) developed a solution strategy that addresses the challenges of scheduling electric buses, fleet configuration, and charging infrastructure optimization. The strategy aims to reduce the total cost of operation, which includes the cost of the vehicle, the cost of the charger, the cost of operation, and the cost of energy, utilizing GA and a mixed integer linear programming formulation. Yang et al. (2019b) proposed a data-driven strategy to improve the current charging station configuration, considering government planning constraints such as quantity, overflow, and usage of charging stations. The ET trajectory dataset, POIs, station data, and road network data are four data sources that can be used to determine the regularity of urban charging behavior. Kang et al. (2016) presented an integrated decision-making framework that employs a multidisciplinary optimization model to assess the profitability of a cooperative business model. Li et al. (2016) proposed a heuristic based on GA to solve a multi-period, multi-path refueling location model, which determines the cost-effective station rollout method on both spatial and temporal dimensions, capturing the dynamics of the network's topological structure. The optimum design for an electric vehicle charging station (EVCS) is provided in this study by Hafez and Bhattacharya (2017) with the aim of reducing lifecycle costs while accounting for environmental emissions.

EV charging stations are necessary, in order to allow electric vehicles to be fully charged during its travels. Since charging EVs is a time-consuming process, It is also essential to make sure parking spaces and post-charging areas are available and secure to ensure all customers can charge their vehicles. There is a need to look at which parking issues EV charging stations deal with. He et al. (2018) developed an optimization model for the layout of a charging station using transportation planning theory, utilizing urban parking as a base and basing it on the compatibility with construction cost and user's interest. Zhang and Li (2015) focus on the daytime plug-in electric vehicle charging scenario in parking lots close to commercial establishments, where the majority of vehicles have extended parking times. The best pricing approach is determined using a two-stage approximate dynamic programming framework that takes into account both long-term estimation from historical data and expected

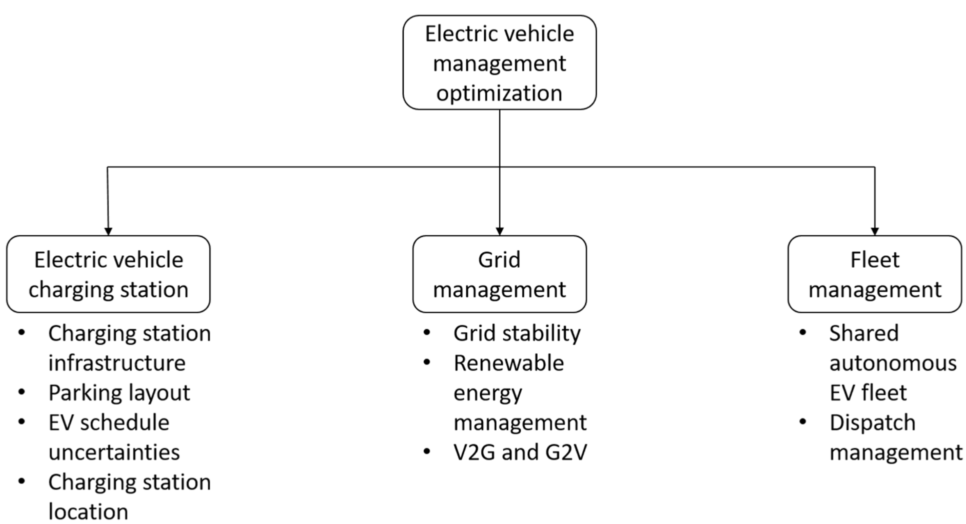


Fig. 13 Overview of electric vehicle charging ecosystem

short-term future information. The centralized electric vehicle (EV) recharge scheduling system for parking lots that Kuran et al. (2015) suggested in this study is based on a realistic vehicle mobility/parking pattern and is targeted at specific parking lots. Regarding two objective functions, the authors evaluate the performance of the suggested system in comparison to two well-known basic scheduling mechanisms, first come, first served and earliest deadline first: (1) maximizing parking lot revenue overall and (2) maximizing the total number of EVs meeting requirements.

4.1.2 Uncertainty management in EV charging optimization

Uncertainties in operational parameters of an EV and the charging station affect the performance and need to be addressed in the optimization formulation. Bi et al. (2021) suggested using a two-stage stochastic optimization model to jointly optimize the distribution of EV flows and the placement of chargers to reduce the predicted total journey time for EVs under stochastic traffic conditions. The model determines the sufficiency of charging resources by statistically predicting a lower bound for the number of chargers to allocate, which helps to avoid overinvesting in charging resources. Bagherzadeh et al. (2020) proposed the long-term durable profit for charging station (DPCS) algorithm, which uses a stochastic optimization framework to increase the long-term profit of the charging station owner. The charging station owner can choose the electricity sales price, vehicle admittance, and number of operational pumps at each time interval using the DPCS algorithm. Rasouli et al. (2019) presented a new model based on the Monte Carlo simulation method for estimating the uncertainty of EV charging station load in a day-ahead operation optimization of a smart microgrid. The uncertain factors considered include battery capacity, type of EVs, state of charge, charging power level, and response to energy price changes. Quddus et al. (2021) offered a unique disruption prevention model to construct and operate a network of EV charging stations under unknown power demand. Their model takes into account both long-term expansion decisions and short-term operating decisions and includes a nonlinear term to prevent the evolution of excessive temperature on a power line under various external conditions. Wu et al. (2022) presented an ideal parameter forecasting technique to increase the forecasting precision of EV charging demand in microgrids. Their approach changes the ideal parameter values of probability distributions within fuzzy sets based on feedback from EVs that have arrived in the microgrid and computes average values of several sample data to increase the stability of forecasting outcomes.

4.1.3 Charging station location optimization

The strategic location of charging stations is crucial to minimize infrastructure investment while optimally fulfilling the charging demand of an area. Awasthi et al. (2017) proposed a hybrid algorithm based on GA and an upgraded from of traditional PSO to determine the best charging station location with minimal impact on the utility grid. The algorithm functionality is improved, and solution quality is increased by re-optimizing the received sub-optimal solution (site and station size) using PSO. Yang et al. (2017) provided a data-driven optimization approach for the allocation of chargers for battery electric vehicle (BEV) taxis throughout a city with the aim of minimizing infrastructure investment. A queueing model is used to assess the likelihood of BEV taxis being charged at their dwell locations while considering charging congestion. Huang and Zhou (2015) proposed an integer programming-based optimal methodology for workplace charging methods that specifically addresses various eligible levels of charging technology and employee demographic distributions to meet all charging demand. The optimization model aims to reduce the lifespan cost of machinery, installations, and operations. Baouche et al. (2014) proposed a method for determining the optimal placement of charging stations by modifying a linear model based on two traditional location models. The model focuses on minimizing the total journey cost from demand zones to the charging station site, along with the server investment cost, rather than restricting the charging stations to designated demand zones. To address the charging station location problem, Kong et al. (2017) proposed a three-layered system model of fast charging stations. The first layer identifies the locations of the charging stations, the second layer uses a queuing model and introduces a resource allocation framework to optimize grid resources, and the third layer considers the battery charging dynamics and develops a station policy to maximize profits by setting maximum charging levels. Liu et al. (2012) proposed an adaptive PSO algorithm to determine the optimal location and scale of EV charging stations, considering geographic information, construction cost, and running cost. Xi et al. (2013) created a simulation–optimization model that identifies the best locations for charging stations for privately owned EVs, and demonstrates that using both level one and level two chargers is preferable to using solely level two chargers. Erdinc et al. (2018) proposed a novel idea that considers the sizing and positioning of wind and solar-based renewable distributed generation units, various types of EV charging stations servicing various end-user groups, and energy storage system (ESS) units for distribution systems. Vazifeh et al. (2019) developed an innovative data-driven strategy to optimize the placement of EV charging stations, aiming to cover the whole demand region while minimizing drivers' total excess driving distance to reach charging stations, the associated energy overhead, and the number of charging stations.

4.2 Grid management

Grid management is a strategy for managing the supply and demand of electricity in electrical systems. It is necessary for charging stations to deliver reliable and economical supply in response to EV charging demand. Grid management is a system management approach that takes into account the variability of electricity supply or demand.

4.2.1 Grid stability management

In their description of the fundamental operations of an electric car charging service provider, Sundstrom et al. (2011) focused on optimization issues related to EV charging service providers and demonstrate a novel approach that considers voltage and power grid limits in the planning of EV charging. The technique creates a unique charging strategy for each car, prevents grid congestion, and meets the demands of vehicle owners. Hashim et al. (2021) proposed a priority-based vehicle-to-grid scheduling to reduce grid load variance, optimizing the quantity of charging/discharging power based on the state of charge of the EV battery. Tan et al. (2016) also presented an ideal vehicle-to-grid scheduling that utilizes GA to reduce power grid load variance by allowing grid-to-vehicle charging of EVs when the actual power grid loading is lower than the target loading and conducting vehicle-to-grid charging when the actual power grid loading is higher than the target loading.

Grid management becomes more crucial for charging stations, particularly those using renewable energy sources due to the fluctuation in their output. Several studies have focused on managing this instability. Petrusic et al. (2020) proposed a technique to simultaneously optimize the charging/discharging of ESSs and EV charging power of a charging station with renewable energy source. Sun et al. (2021) proposed the optimization of the capacity and charging strategy of a charging station that combines wind and photovoltaic (PV) power while considering costs and emissions as objective functions. Wahedi et al. (2022) assessed the economic viability of a novel charging station that includes a PV system, wind turbine, converter, electrolyzer, backup bio generator, and H2 and NH3 fuel cells hybridized with electrochemical and chemical storage facilities.

4.2.2 Renewable energy management

EVs offer eco-friendliness as an advantage, but it's essential to note that this eco-friendliness depends on the greenness of the power source that charges them. Nonetheless, renewable energy generation faces the challenge of variability in power production. Therefore, there are studies to integrate the uncertainties of EV electricity use and renewable energy generation. Rezaei et al. (2020) simulated what changes each would bring to the model when EV demand uncertainty, renewable energy generation uncertainty, and market price uncertainty were considered. Poursmaeil et al. (2021) propose an optimal scheduling model that considers both uncertainty of renewable energy generation and market price uncertainty.

Of the different renewable sources, PV power generation is one of the most actively investigated and promising areas. As a result, numerous research on the grid management of charging stations using PV power generation has been carried out. Chaudhari et al. (2018) optimized the charging/discharging of a charging station with ESS, PV, and grid, taking into consideration changing wholesale power prices, dynamic electricity consumption, and ESS degradation. Dai et al. (2019) also explored the optimization charging stations that encompass ESS, PV, and grid, taking into account the size of the ESS and PV, as well as charging and discharging strategies. Eldeeb et al. (2018) suggested multi-objective optimization, which takes into account both the lifetime of the ESS and the PV charging station's profit. Mohamed et al. (2020) proposed the optimization of power-flow regulation in a charging station integrating PV and grid, with an objective function of the variation in DC-bus voltage during EV charging, in order to lessen the risks associated with solar energy production.

4.2.3 V2G and G2V energy transfer management

To address the unstable electricity demand of EVs, some grid management strategies such as vehicle to grid (V2G) and grid to vehicle (G2V) involve integrating the demand with the electricity of commercial buildings. While this integration can make the system more complex, it can also increase the stability and cost-effectiveness of the electrical system. Quddus et al. (2018) proposed optimizing a system that combines office buildings, charging stations, and the grid in the presence of uncertain power demand. Yang et al. (2019b) suggested optimizing a system that combines grids for commercial buildings and wind power. Yan et al. (2019) proposed optimizing the charge/discharge strategy in a charging station that combines PV, grid, and commercial building, where the EV charging price and vehicle-to-grid bonus price are controlled over time.

4.3 Fleet management

4.3.1 Fleet management of shared autonomous electric vehicles

Fleet management is an important aspect of shared autonomous electric vehicles (SAEVs), which combines autonomous driving technology and car-sharing services while producing zero emissions. As SAEVs are expected to become integral parts of transportation systems in the near future, managing an SAEV fleet requires establishing connections between fleet operations, charging station operations, powertrain requirements, consumer demand, and company profit. Kang et al. (2016) presented a multidisciplinary framework to quantitatively analyze the effect of government public policies on the EV market by modeling the decisions of government, manufacturers, charging station operators, and consumers. They examined three business model scenarios for the EV markets in the cities of Ann Arbor and Beijing that have different stakeholder characteristics. They concluded that their quantitative analysis could help policy makers examine the impact of subsidy budget levels and policies while considering all stakeholders' interests. Kang et al. (2017) presented a system design optimization framework that integrates four subsystem problems: (1) fleet size and assignment schedule, (2) number and locations of charging stations, (3) vehicle powertrain requirements, and (4) service fees. They found that the developed decision framework for autonomous fleet assignment, charging station location, and powertrain design can result in low wait time for customers and a stable service under different market simulations. They also compared an autonomous vehicle service that uses EVs to one that uses gasoline engines, and provided practical insights for service system decision makers. Kim et al. (2022) proposed a deep learning-based algorithm that can instantly predict the optimal solution to idle vehicle relocation problems under various traffic conditions. They validated their proposed idle vehicle relocation model by applying it to the optimization of an SAEV system. They showed that their proposed strategy can significantly reduce operation costs and wait times for on-demand services.

Lee et al. (2019) proposed a reliability-based design for market systems (RBDMS) framework by integrating reliability-based design optimization (RBDO) and design for market system approaches to find the optimal target reliability that maximizes company profit. They applied the proposed framework to EV fleet design problems to explore the effect of the target reliability on company profit and engineering performances of EVs. Lee et al. (2020) considered uncertainties in an SAEV system and applied RBDO to the design of the SAEV fleet system. They compared the optimization results of various wait time constraints and probabilities of failure and provided observations on applying RBDO to the design of an SAEV system. Lee et al. (2022) presented a design framework for a shared autonomous fuel cell electric vehicle (SAFCEV) based on a proton-exchange membrane fuel cell model. They optimized a shared autonomous battery electric vehicle (SABEV) and an SAFCEV to minimize the total cost while satisfying the customer wait time constraint. They found that the SAFCEV system had a 9.8% smaller fleet size and 108.8% larger driving range compared to the SABEV system. They also found that a hybrid fleet system that simultaneously operates SABEV and SAFCEV could lead to a total cost reduction of 0.8% compared to the case when only SAFCEV is operated.

4.3.2 Optimization in dispatch management of EV fleet

In the public transportation domain, efficient management of EV fleets is essential to maximize its utilization while minimizing the infrastructure development cost and operational cost for given input characteristics of each EV. EV dispatch planning depends on various parameters such as number of EVs, their battery capacity, weather, route, driving conditions among others.

Brooks et al. (2010) discussed the prerequisites for demand dispatch, including communication and control over the internet, as well as fast reaction times for load-based auxiliary services. Smart charging is cited as an example of demand dispatch as it relates to plug-in EVs. To account for the unpredictability of wind turbines and plug-in electric vehicles, Zhao et al. (2012) presented an economic dispatch model that uses PSO and interior point techniques. Gendreau et al. (2006) proposed neighborhood search heuristics to improve the scheduled routes of vehicles in a situation where new requests with pick-up and delivery locations are made in real-time. They investigate new solutions within this framework using a neighborhood structure built on ejection chains. In a multigraph where multiple travel possibilities are represented by parallel arcs between pairs of vertices based on factors such as time, cost, and distance, Lai et al. (2016) studied a time-constrained heterogeneous vehicle routing problem. They present the problem as a mixed-integer linear programming model and devise a tabu search heuristic that effectively handles the concurrent arcs' impact on computation. With a mixed fleet of electric and diesel buses and a limited number of chargers, Alvo et al. (2021) investigated how to efficiently manage a bus dispatch operation at a public transportation terminal. They reformulated the problem into two subproblems: a master problem that allocates bus travel itineraries and a satellite problem that sequences charging tasks. This problem is described as an extension of the vehicle scheduling problem, and the branch-and-bound tree is dynamically modified using the exact decomposition approach to eliminate bus trip plans that would result in an impractical bus charging procedure. Zhao et al. (2012) proposed a bi-objective programming approach using NSGA II to solve a vehicle routing problem with a mixed fleet of conventional and electric cars, with the aim of reducing operational costs and time penalty costs. Reinforcement learning (RL), a model-free and online learning technique, can capture a variety of uncertainty through repeated encounters with the environment and instantly adjust to different state situations. Qiu et al. (2023) summarizes how single-agent RL and multi-agent RL are two of the most widely used RL algorithms and how they can be used to solve a variety of EV dispatch issues.

4.4 Summary

Charging station management involves ensuring the effective operation of charging stations and maximizing the utilization of the charging infrastructure while minimizing the total operational cost. This includes addressing issues such as selecting the optimal location for charging stations that can meet the area's charging demand with the least amount of infrastructure investment, and optimizing the operation of charging stations to minimize the total operating cost. Need of optimal parking layout for EV charging stations is also discussed. The impact of uncertainty in EV operation on charging station management was also discussed. EV charging places a strain on the power grid and may pose potential threats to the power grid reliability by overloading grid equipment and disturbing grid voltage stability. Strategies to stabilize and manage the grid were discussed to reduce the grid congestion. To deal with power output uncertainty from renewable energy sources, charging strategies were explored, including the use of ESSs and integration of various renewable energy sources into charging stations along with their economic viability. Fleet management techniques were also reviewed to minimize infrastructure and operational costs, and optimization algorithms and heuristics were discussed to solve problems such as dispatch and scheduling. Operation problems of mixed fleet routing were also discussed. In recent years, the management of autonomous fleets, which involves various entities of an EV operation, has gained traction. An extensive review of reliability-based design of shared autonomous electric vehicles to minimize the total cost was also discussed.

5 Conclusion

Current challenges related to climate change are driving the need for more efficient EVs. Although significant progress has been made in EV technology at both the component and system level, there is still a gap in comprehensive surveys of optimization studies related to EVs. To address this gap, the current work provides a comprehensive survey of optimization developments in different aspects of EV. The survey covers optimization of the battery, including thermal, electrical, and mechanical aspects. Thermal optimization aims to manage heat through techniques such as air or liquid cooling, while electrical optimization focuses on managing charging with discussions on coordinated and uncoordinated charging and their respective advantages and disadvantages. Mechanical optimization focuses on characteristics such as light-weighting, vibration insulation, and collision resistance. Future studies should focus on developing system frameworks that address all three aspects while accommodating new designs made possible by advanced techniques such as generative design or origami-inspired topological designs enabled by additive manufacturing. Such frameworks should also permit sensitivity studies of battery performance with alternate materials and incorporate sustainability considerations. Finally, while many optimization studies focus on performance, further research on robustness, reliability, and sustainability is needed to justify the use of EVs.

Next, strategies for battery charging/discharging and battery swapping are reviewed, taking into consideration factors such as operation, cost, battery performance, and range anxiety. The use of wireless strategies to enable faster charging is also discussed, with optimization techniques mainly focusing on topology or network optimization using heuristics techniques. Future research should address uncertainties in charging ecosystem design and incorporate both forward and inverse prediction capabilities to leverage benefits for both the grid and individual vehicles. Advanced machine learning techniques such as transfer learning can be developed to arrive at predictions faster, enabling almost instant alerts or guidance for charging. Additionally, future research should explore advanced techniques such as graph partitioning for geo-partitioning to better understand time series of battery usage for improved predictions and forecasting while accounting for uncertainties.

This survey also discusses optimization techniques of other EV components, such as motors, powertrains, tires, and chassis. Currently, powertrain configuration optimization is performed separately from parameters optimization and control system optimization, resulting in sub-optimal EV designs. Future research should focus on simultaneous optimization of configuration along with size and control parameters exploration to address the issue. While batteries, battery management systems, drivetrains, and motors have received the most attention in EV design optimization studies, other sections including the body, chassis, suspension system, and tires have also been the subject of design and optimization research.

Finally, this work presents a review of the EV ecosystem, specifically the optimization of charging station, grid, and fleet management. Research on charging station construction, charging station operation strategies, and power system operation strategies are discussed.

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Declarations

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