

Electric Vertical Takeoff and Landing Aircraft Charging Demand Modeling and Integration into Power Distribution Networks: A Comprehensive Review

Tao Qian, *Member, IEEE*, Yangyimiao Sun, *Graduate Student Member, IEEE*, Hongxun Hui, *Member, IEEE*, Qinran Hu, *Senior Member, IEEE*, Zaijun Wu, *Senior Member, IEEE*

Abstract-- Electric vertical takeoff and landing aircraft (eVTOLs) are expected to play an important role in future urban air mobility (UAM) and introduce high-power charging loads to urban power systems. This paper reviews eVTOL charging load modeling and forecasting methods, with particular emphasis on distribution network impacts, grid planning, and coordinated operation. First, the charging load formation mechanism of a single eVTOL is analyzed from the perspectives of flight energy consumption and charging strategies, with emphasis on the key factors affecting charging demand. Second, the operational uncertainty and charging scheduling methods of aggregated eVTOL charging loads at vertiports are discussed, followed by an analysis of urban-scale spatiotemporal charging load modeling and forecasting. Finally, the paper summarizes the impacts of high-power eVTOL charging loads on distribution networks, and discusses infrastructure planning, network control methods, and coordinated flexibility management. This paper summarizes current research progress and, by comparing relevant methods developed for EV charging, identifies future research directions for mission-driven charging load modeling and the coordinated operation of power grids and three-dimensional transportation systems.

Index Terms-- Electric vertical takeoff and landing (eVTOL) aircraft, Energy consumption, Charging demand modeling, Urban air mobility (UAM), Charging strategy.

I. INTRODUCTION

As urbanization accelerates, Urban Air Mobility (UAM) has emerged as a promising solution to alleviate ground transportation congestion in densely populated urban areas. Driven by advances in electric propulsion, autonomy, and lightweight materials, electric vertical takeoff and landing (eVTOL) aircraft overcome the need for long runways and are regarded as a key mode of transportation in UAM, offering direct point-to-point connectivity. They can provide lower noise emissions [1], reduced operational costs, and zero local carbon emissions compared with conventional helicopters, making them more suitable for large-scale urban deployment. Recent policy documents have clearly promoted their pilot

deployment and commercial application. For example, China supports the development of short-haul transportation and eVTOL passenger networks, and aims to foster a trillion-yuan low-altitude economy market by 2030 [2]. In the United States, the Federal Aviation Administration identifies eVTOL as an important component of Advanced Air Mobility (AAM), and highlights vertiport charging and electrical infrastructure as key issues for AAM deployment [3]. Similarly, the European Commission promotes innovative air mobility services, including air taxis, and develops regulatory actions for eVTOL aircraft [4]. In the United Kingdom, the Department for Transport targets initial passenger and cargo operations for eVTOL aircraft by 2028 [5]. These official roadmaps provide strong policy support for the future large-scale deployment of eVTOLs.

Unlike ground electric vehicles (EVs), the charging requirements of eVTOLs are typically characterized by high-power demands, tightly coupled with flight missions, turnaround constraints, and vertiport scheduling [6]. Recent studies evaluate the effects of concentrated eVTOL charging on distribution networks, highlighting potential voltage violations and capacity constraints at vertiports [7]. Moreover, the charging demand of an eVTOL is directly influenced by flight distance, payload, environmental conditions, and operational uncertainties such as hovering, rerouting, and delay, which introduce strong temporal variability and uncertainty into the charging demand. As a result, accurate modeling is essential.

EV charging demand is typically driven by ground traffic mobility patterns and user behavior, with relatively flexible charging windows. The methodologies are generally categorized into two types: model-driven and data-driven techniques. Model-driven methods usually employ mathematical models, such as stochastic charging load models [8] and user equilibrium models [9], to characterize EV charging behavior. These methods are interpretable and suitable for scenarios where historical charging data are limited, but their accuracy strongly depends on assumptions regarding travel behavior and charging rules. In contrast, data-driven

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T. Qian, Y. Sun, Q. Hu and Z. Wu are with the School of Electrical Engineering, Southeast University, Nanjing 210000, China.

H. Hui. is with the State Key Laboratory of Internet of Things for Smart City, University of Macau, Macau, China.

approaches forecast EV charging demand from historical charging records and related contextual variables,

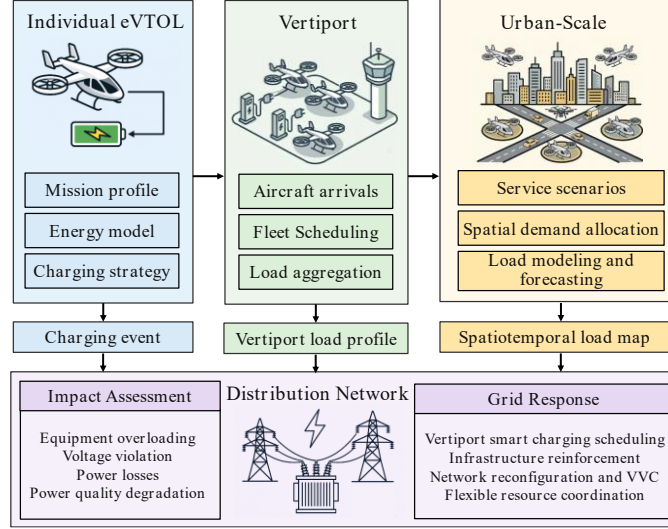


Fig. 1. Multi-scale review framework

without explicitly modeling vehicle dynamics or individual behavior. Representative studies have applied PSO-SVM [10], context-aware temporal transformer models [11], and other machine learning (ML) methods [12] to short-term or hourly EV charging demand forecasting. These studies demonstrate the ability of data-driven methods to capture nonlinear temporal patterns and improve forecasting accuracy when sufficient historical data are available. However, these methods rely on mature EV charging datasets and provide limited representation of operational constraints. Therefore, they cannot be directly applied to eVTOL charging demand analysis at the early development stage, where large-scale real operational data are still unavailable.

In contrast, eVTOL charging demand studies are still mainly based on scenario analysis and mechanism modeling. Existing studies usually estimate aircraft energy use from mission profiles or trajectory information, and then translate it into charging demand at charging stations [13]-[16]. However, they often focus on individual parts of the modeling chain. The formation mechanism of charging loads under fleet-level eVTOL operations, especially with heterogeneous aircraft types, has not been sufficiently clarified.

Recent review studies address eVTOL issues from different perspectives. Several surveys focus on autonomy and navigation, reviewing perception, planning, and control architectures and outlining future research through autonomy levels and integration challenges [17], [18]. Others focus on flight control [19], safety [20], and environmental impact, such as noise prediction and mitigation [21]. Other reviews concentrate on onboard power systems, including thermal management [22], battery degradation [23], and hybrid-electric energy management [24], with limited explicit discussion of electric charging and power grid integration. In these studies, charging demand characterization is not treated as a primary review dimension. As shown in Fig. 1, this review follows the formation of eVTOL charging loads across multiple levels. It starts from individual eVTOL charging demand modeling, then

moves to vertiport load aggregation and urban load forecasting, and finally discusses distribution

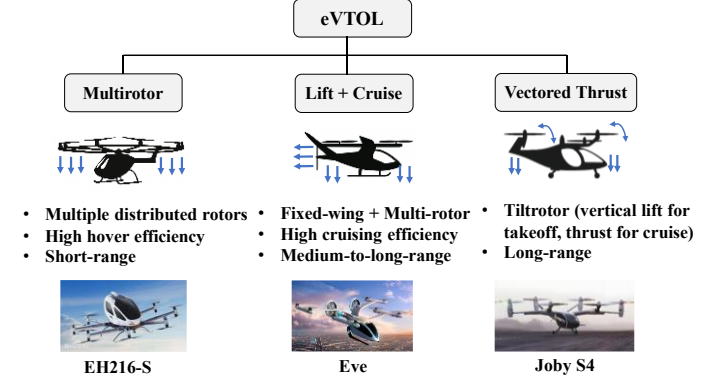


Fig. 2. eVTOL Configurations

network impacts and active scheduling for grid integration. It provides a systematic review with the following key contributions:

- 1) Reviews eVTOL charging demand modeling methods from the perspectives of flight energy consumption and charging strategies. The key factors affecting charging load formation under different flight phases and operating conditions are analyzed.
- 2) Discusses the formation and uncertainty sources of charging loads in large-scale eVTOL operations. Vertiport charging load management methods and urban-scale charging load forecasting methods and challenges are emphasized.
- 3) For the coupling problem between future power grids and urban three-dimensional transportation networks, this paper summarizes planning, active scheduling methods and challenges for distribution networks to address high-power eVTOL charging loads.

II. CHARGING DEMAND MODELING FOR AN INDIVIDUAL eVTOL

As eVTOLs operate differently through distinct mission phases, their power requirements vary significantly across the flight profile, making charging demand highly sensitive to multiple factors. These include airframe structure, weight, route planning and environmental conditions such as wind, temperature, and air density. Rigorous analysis of these determinants is essential, and the accuracy of fleet-level load forecasting for eVTOL ultimately depends on the fidelity of individual aircraft energy models.

A. eVTOL Design and Configuration

Configuration is an important factor for analyzing the charging load formation of large-scale heterogeneous eVTOL fleets. Existing conceptual design and mission analysis studies indicate that different eVTOL configurations lead to different aerodynamic characteristics, propulsion architectures, and power requirements [25]. The suitable configuration is closely related to payload and mission range in a UAM mission [26], [27]. According to the website Electric VTOL News [28],

published by the Vertical Flight Society, eVTOL aircraft are categorized into the following types based on their thrust types: wingless (multirotor), lift + cruise, vectored thrust, hover bikes & personal flying devices, and electric helicopters. This subsection provides a detailed analysis of three main eVTOL categories, as depicted in Fig. 2, and their performance during various flight mission phases.

Wingless multirotor eVTOLs rely on multiple distributed rotors for vertical lift and propulsion. Their large rotor disk area generally leads to lower disk loading and better hover efficiency [29], [30], making them suitable for short-range urban missions with frequent vertical operations [30], [31], [32]. This configuration also has advantages in compactness and structural simplicity [29], which are important for early-stage UAM deployment. In contrast, lift + cruise eVTOLs separate vertical lift and horizontal propulsion by using dedicated lift rotors for takeoff and landing and fixed wings for cruise flight. This configuration improves cruise efficiency, but the non-operating lift rotors and supporting structures may introduce additional weight and drag during cruise [30], [32]. Vectored-thrust eVTOLs integrate fixed wings with tilting propulsion systems, using the same propulsion system for both vertical lift and forward thrust. This configuration benefits from higher cruise efficiency and is more suitable for longer-range missions [25], [30].

Overall, different eVTOL configurations correspond to different application scenarios and charging requirements. This means that eVTOL charging demand should not be represented by a single typical aircraft. Instead, heterogeneous fleet composition and mission assignment should be considered.

B. Aerodynamic Model

The flight mission profile for the eVTOL aircraft follows a typical UAM mission, comprising several key phases: startup, vertical takeoff, transition & hover, climb to cruising altitude, cruise flight, descent, hover again, landing, shutdown, and finally, recharging and passenger boarding. The total battery energy required for a single eVTOL trip can be calculated by integrating the specific power required over time for each flight phase, as in (1).

$$E = \sum_i P_{bat,i} T_i \quad (1)$$

where $P_{bat,i}$ and T_i are the output power and discharge time of the battery during the i -th stage respectively, including hover, climb, cruise and descent.

The power required during takeoff and hover is modeled using momentum theory, as shown in (2) [33].

$$P_{hover} = \frac{mg}{\eta_h} \sqrt{\frac{\sigma}{2\rho}} \quad (2)$$

where mg is the takeoff weight of the eVTOL. η_h is the hover system efficiency, σ is the disk loading and ρ is the air density.

In climb and descent phases, the required power is modeled in (3) [33].

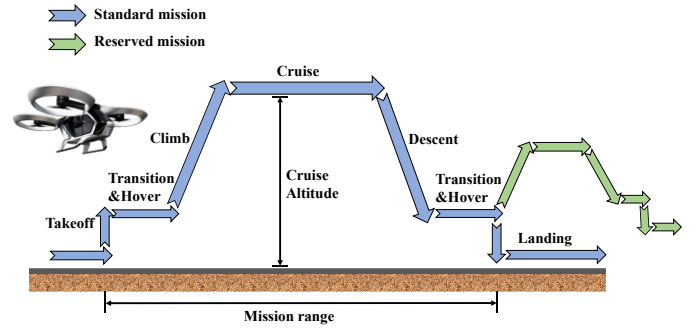


Fig. 3. eVTOL flight mission profile

$$P_{climb} = \frac{mg}{\eta_{climb}} \left(V_{climb} \sin \gamma + \frac{V_{climb}}{L/D_{climb}} \right) \quad (3)$$

$$ROC = V_{climb} \sin \gamma \quad (4)$$

where η_{climb} is the climb system efficiency, V_{climb} is the true air speed, which is calculated using the flight path angle γ and the assumed rate of climb ROC, as in (4). L/D_{climb} is the lift-to-drag ratio.

Cruise flight is modeled using a simple force balance and the power required is modeled in (5).

$$P_{cruise} = \frac{mg}{\eta_{cruise}} \frac{V_{cruise}}{L/D} \quad (5)$$

where η_{cruise} is the cruise system efficiency, V_{cruise} is the cruise true air speed, L/D is the lift-to-drag ratio.

This formulation retains the key variables governing mission energy use while relying on aggregate aerodynamic parameters rather than detailed vehicle geometry. It does not require large training datasets. Other energy models, such as trajectory-based models, estimate energy consumption through flight path simulation and can capture rerouting, additional hovering and non-nominal operations [14]. They require detailed scenario settings and higher computational effort. Data-driven models predict energy use from operational and environmental samples [34]. Therefore, the adopted model provides a suitable balance between model fidelity and complexity for charging demand analysis.

Moreover, reserve capacity is critical in eVTOL operations to ensure safety during unexpected circumstances such as weather changes, air traffic diversions, or technical issues. The FAA's IFR fuel reserve requirement mandates an additional 30 minutes of flight at normal cruising speed for helicopters [35]. Uber suggests a more tailored approach for eVTOLs, proposing a reserve capacity that allows for a 6-minute diversion to an alternate landing site [36], [37]. Some studies advocate for a reserve capacity of approximately 20% of the total battery capacity [33], [38].

C. Planning for eVTOLs

Planning methods determine the operational inputs used in energy calculation, such as route length and flight speed. They are also closely related to charging demand uncertainty, as

obstacle avoidance, airspace restrictions, and rerouting may change mission energy consumption and the subsequent charging requirement. Existing planning methods can be generally divided into path planning and trajectory optimization.

Path planning generates feasible routes in low-altitude airspace. Representative methods include graph-search [39], [40], sampling-based [41], [42], metaheuristic [43]-[45], and hybrid algorithms [46]. For charging demand modeling, path planning mainly determines the spatial and temporal features of a mission.

Trajectory optimization further refines the planned route into a safe, smooth, and executable flight trajectory [47]. Existing methods can be divided into hard-constrained and soft-constrained formulations. Hard-constrained methods explicitly impose safety, collision avoidance, and dynamic feasibility as equality or inequality constraints, such as minimum-snap trajectory generation [48], safe flight corridors [49], and sequential convex programming [50]. Soft-constrained methods incorporate performance requirements into the objective function through penalty terms, such as CHOMP [51], STOMP [52], continuous-time trajectory optimization [53], and B-spline-based methods [54]. A planned path mainly describes the geometric route between vertiports, including waypoints, route distance, detour length, and corridor connectivity. Trajectory optimization further adds time and dynamic feasibility to the planned route. It determines speed profiles, climb and descent rates, turning behavior, transition duration, and transient power demand. These outputs affect eVTOL energy consumption, arrival state-of-charge (SOC), and the charging energy required after landing.

Overall, planning methods can be coupled with aerodynamic energy models to obtain more realistic mission energy estimates. High-fidelity trajectory optimization or control simulation can further provide detailed thrust and power profiles, but its computational cost limits direct use in large-scale charging load studies. Future eVTOL charging demand models should balance planning fidelity and scalability.

D. Key Factors Affecting eVTOL Energy Consumption

Based on the aerodynamic model and planning methods, the key variables affecting eVTOL energy consumption can be divided into three groups: aircraft parameters, mission variables, and external operating conditions.

Aircraft parameters determine the basic energy requirement of a flight. For heterogeneous eVTOL fleets, payload should be given particular attention. Passenger transport, cargo delivery, and emergency logistics usually correspond to different payload levels and mission patterns. These differences lead to variations in energy consumption and charging demand. Therefore, payload should not be regarded only as a fixed aircraft parameter, but should be incorporated as an operational variable in charging demand modeling.

Mission variables mainly include cruise speed and cruise altitude. Cruise speed requires a balance between energy consumption and flight duration. Xie et al. [55] showed that optimizing the velocity profile can significantly reduce energy

consumption. Kang et al. [56] further provided a minimum-energy speed profile for tiltrotor eVTOL aircraft under specific time constraints. Cruise altitude also affects energy use. Existing studies indicate that energy consumption varies with altitude because induced drag and parasite drag change under different flight conditions [34]. Li *et al.* [57] observed that minimum energy consumption may occur at certain altitudes due to this tradeoff.

External operating conditions mainly include wind, air density, and ambient temperature. Wind has a direct effect on mission energy consumption because it changes the relationship between airspeed and ground speed. Headwinds can greatly increase flight time and energy use, and may cause two to three times higher energy consumption than tailwinds in short urban flights [58]. Air density also affects lift generation. Lower air density reduces lift and increases the required thrust, which increases energy consumption [34]. This is closely related to cruising altitude, as mentioned above. Ambient temperature affects both flight energy use and battery behavior. It changes battery efficiency in the short term and accelerates battery aging in the long term. In extreme urban environments, temperature variation and battery degradation may become important factors limiting eVTOL performance [59]. Therefore, external operating conditions should not be treated only as background parameters. They affect the energy that must be replenished after each mission, the reserve margin before departure, and the feasible charging power under battery thermal limits.

Overall, these variables may affect recharge energy, feasible charging power, and charging duration. Their representation in charging demand models should be selected according to the research scenario, since a more detailed description can improve accuracy but also increase model complexity.

E. Charging Strategies for Single eVTOL

Once the recharge energy required by an individual eVTOL is determined, an appropriate battery charging strategy is needed to translate this requirement into a charging power profile. Common charging strategies include constant current-constant voltage (CC-CV) charging, multi-stage constant current-constant voltage (MCC-CV) charging, constant power-constant voltage (CP-CV) charging, pulse charging (PC), boost charging, and variable-current charging (VCC).

Among these, CC-CV charging is the most widely used strategy. A publicly available eVTOL battery dataset adopts CC-CV charging as the standard charging process between flight missions [60]. Battery health prediction studies based on this dataset also treat charging as an important phase in the complete eVTOL mission profile [61]. MCC-CV charging uses multiple constant-current stages followed by a final constant-voltage stage [62]. By adjusting the current level and switching threshold of each stage, it can improve the tradeoff among charging time, energy efficiency, thermal behavior, and battery aging. CP-CV is suitable for high-power charging scenarios because it limits input power during the early charging stage and retains the voltage-limited termination process [63]. For vertiports, this feature can help reduce transient grid impacts

while maintaining compatibility with battery-side charging requirements. Other strategies, such as pulse charging, boost charging, and variable-current charging, remain mainly at the cell or laboratory level. Their application to certified eVTOL operations still requires validation under high-power, thermal, and aging constraints.

Furthermore, in many studies, the charging process is often simplified as a prescribed charging profile. This simplification may be acceptable when charging power is moderate and the battery has sufficient rest time between cycles. However, its validity becomes weaker for eVTOL operations. Compared with ground EVs, which generally charge less frequently and remain parked for longer periods, eVTOLs may require multiple high-power charging events within a single operating day. Therefore, the charging strategy cannot be decoupled from battery thermal management and aging behavior. In single eVTOL charging demand modeling, the key issue is not only the nominal charging protocol, but also the effective charging power allowed under thermal and aging constraints. High-power charging may require active cooling, current derating, or longer turnaround time. Ignoring these effects may overestimate feasible fast-charging capability and underestimate charging duration and long-term battery cost.

III. LARGE-SCALE EVTOL CHARGING DEMAND MODELING AND FORECASTING

This section further extends the analysis from single aircraft charging behavior to large-scale charging load formation. At the vertiport level, aggregated charging demand is affected by flight schedules and operational uncertainties. At the urban level, service scenarios and spatial demand patterns determine where and when charging loads emerge. Therefore, this section reviews vertiport charging load aggregation, charging scheduling strategies, and urban-scale charging demand modeling and forecasting, providing a basis for subsequent distribution network impact and scheduling analysis.

A. Vertiport Charging Load Aggregation and Uncertainty Characterization

At the vertiport level, fleet charging demand originates from the aggregation of individual eVTOL charging events. This aggregation determines the potential charging pressure that a vertiport must accommodate before detailed charging scheduling is performed. The actual load profile delivered to the distribution network is also affected by the charging scheduling adopted at the vertiport, which is discussed in the next subsection. This subsection mainly focuses on the flight and operational uncertainties involved in vertiport charging load aggregation.

The uncertainty of vertiport charging demand first arises at the level of individual aircraft and mainly includes operational disturbances and weather conditions. Operational disturbances include temporary rerouting, additional hovering, landing queueing, and short-term airspace restrictions. Once

meteorological data are available, weather conditions, especially strong winds, can be analyzed through aerodynamic models to determine their effects on the operation of different flight phases, as well as on final energy consumption and arrival time. Existing flight simulation datasets in the field of aeronautical engineering can also be used, together with data-driven methods, to identify the relationship between different weather conditions and aircraft charging demand. This avoids the need to consider the details of specific flight control processes. Operational disturbances, such as airspace restrictions, can be addressed using the planning methods discussed earlier to obtain updated flight routes and control parameters, which can then be used to calculate the energy consumption of the mission.

For vertiport and grid operation and scheduling, these uncertainties can be described through event-triggered mechanisms, with corresponding probabilistic models established for different events. If sufficient historical operational data are available, the occurrence probabilities of different events and their impact distributions can be further estimated, thereby reducing the errors caused by subjectively assumed probability distributions.

In addition to uncertainties at the individual aircraft level, operational processes at the vertiport can introduce additional fluctuations. Flight delays may cause aircraft to arrive in clusters, while overlapping charging tasks and changes in equipment availability may affect the station load level and its available flexibility. Updates to charging schedules within the vertiport may further alter the actual station load level. Specific methods for addressing these uncertainties in vertiport and distribution network operation and scheduling are discussed in detail later.

B. Charging Scheduling for Vertiport eVTOLs

EV charging scheduling generally adjusts charging time and power according to grid conditions and electricity price signals. The main objectives are to reduce charging costs and peak demand. In contrast, eVTOL charging is subject to hard constraints, including turnaround deadlines, safety reserves, and mission continuity. Its temporal flexibility is therefore more limited. The detailed differences between the two are shown in Table I. Vertiport scheduling must therefore determine aircraft charging plans from their operating states and subsequent missions, under given charging infrastructure and connection capacity. These decisions directly shape the actual charging load of the vertiport.

Existing eVTOL studies usually embed charging within passenger service and fleet operation. Wu and Zhang [64] jointly optimized passenger service and eVTOL charging to reduce passenger waiting time. This study was among the early attempts to include charging decisions in UAM operation. Charging was mainly treated as a turnaround

TABLE I
Comparison between EV Charging and eVTOL Vertiport Charging

Dimension	EV charging station	eVTOL vertiport charging station
Arrival time	Highly stochastic	Highly scheduled
Dwell time	Long (30 minutes to several hours)	Very short (10–30 minutes turnaround)
Charging power level	7 -350 kW	30 kW-2 MW
Consequence of charging failure	Delay / Inconvenience	Mission cancellation / aviation safety risks
User behavior	Price-sensitive	Insensitive to real-time pricing
Battery modeling	Degradation treated as a slow process	Degradation tightly coupled with flight safety

resource for maintaining flight service. Yue et al. [65] further examined how energy and charging constraints affect the reliability of UAM services. Kleinbekman et al. [66] proposed rolling-horizon arrival sequencing under vertiport capacity constraints. Although charging power was not directly optimized, aircraft arrival order affects subsequent charging opportunities. Shon and Lee [67] further incorporated fleet size, vertiport capacity, charging speed, and charging infrastructure into an integrated UAM operation framework. They also examined the effects of random demand and energy consumption. Wu et al. [68] further linked fleet operation with smart charging. Their method derived charging windows and energy requirements from flight schedules and then optimized charging plans to assess the value of smart charging for grid integration.

Overall, existing studies mainly determine charging opportunities from passenger service and fleet operation. Charging is usually treated as a resource constraint in the turnaround process. Few studies explicitly optimize eVTOL charging. A systematic scheduling framework for eVTOL vertiports is therefore still lacking.

We believe that future research should focus on coordinated scheduling in integrated energy hubs. Early vertiports may be developed by expanding airports, railway hubs, or existing EV charging facilities. Their energy systems may include eVTOL and EV charging, local loads, storage, and distributed photovoltaic generation. Scheduling models should jointly determine eVTOL and EV charging power, storage charging and discharging, renewable energy use, and grid power exchange. The scheduling problem should balance aviation operation, economic performance, and the requirements of the power grid. Flight mission completion and safety requirements should be treated as primary constraints, while station operating costs, peak demand, renewable energy utilization, and vehicle charging performance can be optimized within the feasible operating range.

eVTOLs and EVs should not be modeled as homogeneous flexible loads, since EVs usually have longer parking durations and can provide greater load-shifting flexibility. Vertiport scheduling should also be linked to single aircraft charging models. Aircraft charging power should vary with SOC, temperature, battery health, and thermal management capability.

The study conducted in [69] has begun to coordinate electric aircraft charging with parking EV loads. It converted conventional commuter flights into multiple electric aircraft missions using actual airport schedules. It reduced simultaneous charging peaks by adjusting aircraft arrival times. Aircraft charging loads were then generated from predefined

battery capacities and charging power levels. The study considered airport microgrid energy balance and power exchange with the main grid. However, it did not further model detailed distribution network constraints.

Building on this work, future models should replace predefined aircraft charging profiles with mission-driven charging demand and dynamic power limits. They should also distinguish the service priority and flexibility of eVTOL and EV loads, while incorporating grid capacity, voltage, and equipment operating limits.

C. Urban-Scale Charging Demand Modeling and Forecasting

Modeling and forecasting eVTOL charging loads at the urban level are essential for understanding their temporal and spatial distribution and assessing their impacts on urban power systems. Such analyses provide critical inputs for vertiport infrastructure planning and grid integration studies.

Existing EV studies are reviewed here mainly as methodological references. They can be divided into three groups. The first group reconstructs the load formation process from vehicle travel activities and charging behavior. Liu et al. [70] proposed a data-driven trip-chain modeling framework. It includes travel data processing, EV stock forecasting, trip synthesis, charging demand simulation, and load profile generation. It uses real-world travel data to estimate regional charging demand under different charging scenarios. This approach is useful for generating medium- and long-term load scenarios when complete charging records are unavailable. Zhang et al. [71] further incorporated private EV operating data in Beijing, the urban road network, and the distribution of public charging facilities. Their model jointly simulates vehicle trip chains, charger occupancy, and interactions among vehicles. It predicts the number of charging vehicles and charging power in different urban areas. V2Sim [72] further integrates microscopic vehicle mobility and charging simulation with distribution network analysis, enabling individual EV behavior to be translated into urban charging loads and grid operating states. When complete mobility data are unavailable, Qian et al. [73] jointly estimated EV origin-destination (OD) demand and optimized traffic sensor placement, providing mobility inputs for spatial charging demand analysis under limited observations.

The second group uses traffic assignment models to describe the spatial distribution of EVs across roads and charging stations. Deterministic user equilibrium assumes that all used routes between the same origin and destination have the same generalized travel cost. Stochastic user equilibrium further considers differences in drivers' perceptions of travel time,

congestion, and charging cost. Huang and Kockelman [74] incorporated road congestion, station queues, and charging prices into a user equilibrium model. The model determines vehicle routes, charging station choices, and the spatial distribution of charging demand. The study conducted in [75] further combined stochastic user equilibrium with trip chains. It used an extended Logit model to represent route choice and jointly obtained road traffic states and the spatiotemporal distribution of charging loads. Dynamic traffic assignment further tracks vehicle movements over time across roads and charging stations. Tang et al. [76] integrated trip chains with dynamic user equilibrium. Their model captures route choice, fast and slow charging behavior, and SOC evolution. It also shows how the corresponding charging loads vary over time. Liang et al. [77] further used time-expanded user equilibrium to model the temporal evolution of travel and charging choices.

The third group uses historical charging data for short-term spatiotemporal forecasting. For example, Wang et al. [78] proposed a heterogeneous spatiotemporal graph convolutional network to predict EV charging demand at different temporal and spatial scales. Kuang et al. [79] developed a physics-informed graph learning model that combines charging demand prediction with dynamic pricing. These methods learn spatial correlations among stations and periodic load patterns. They are suitable for short-term scheduling when sufficient operational data are available.

These EV methods also differ in whether the charging station layout is predefined. Trip-based models can estimate regional charging demand without specifying the exact location of each station. In contrast, traffic assignment methods usually assume a given set of charging stations and estimate how vehicles and charging loads are distributed among them. Data-driven forecasting methods also rely on an established charging network and historical observations from individual stations.

For eVTOLs, these conditions are not yet sufficiently established. Vertiport networks have not been widely deployed, and flight and charging data remain limited. Existing EV methods therefore cannot be directly applied to characterize the urban spatiotemporal distribution of eVTOL charging loads. In EV systems, drivers can jointly choose travel routes and charging stations. Traffic assignment combined with charging decisions can therefore determine vehicle arrivals and charging demand at individual stations. In contrast, the large-scale operating pattern of eVTOLs originates from urban service demand but must still be converted into actual aircraft movements through operator task scheduling and fleet dispatch. These processes ultimately determine the spatial and temporal distribution of aircraft and their charging requirements. In addition, eVTOL missions are more diverse. They may include passenger transport, cargo delivery, medical transport, and emergency response, and some missions do not involve passenger travel.

Another key issue is the complex coupling among urban mission demand, ground transportation, and charging loads [80]. The spatiotemporal distribution of service demand largely determines vertiport locations and service coverage, while the charging loads created by flight missions further determine

charger capacity and distribution network expansion requirements. In turn, the vertiport layout affects service accessibility and mission allocation. Charging capability and grid connection capacity may also constrain aircraft turnaround and charging scheduling. Through their effects on operating cost and service quality, these factors may further influence eVTOL demand, operator scheduling, and the resulting charging loads.

Based on these differences, urban-scale eVTOL charging load modeling generally requires a predefined or assumed vertiport network. Unlike EVs, eVTOL arrivals at vertiports cannot be derived from traffic assignment alone. Aviation operation models are needed to provide flight schedules and aircraft arrival information for each vertiport. At the early stage of eVTOL deployment, when large-scale operational data remain limited, existing short-haul flight schedules can be used to construct representative operating scenarios. The resulting flight schedules and aircraft arrivals can be combined with single-aircraft energy and charging models and vertiport scheduling to generate charging load profiles for each vertiport. Aggregating the loads of multiple vertiports across time and space yields the urban-scale charging load distribution under a given operating scenario. As vertiport charging data accumulate, data-driven methods can further learn temporal patterns and spatial correlations among vertiports for short-term forecasting.

IV. DISTRIBUTION NETWORK PLANNING AND COORDINATED OPERATION FOR EVTOL INTEGRATION

The preceding sections mainly introduce the modeling mechanism of eVTOL charging loads, large-scale charging load forecasting, and vertiport charging strategies. This section shifts the focus from the formation of charging load to grid integration. It first discusses the impacts of large-scale eVTOL charging on distribution networks and then reviews distribution network planning and coordinated operation methods.

A. Distribution Network Impacts

As discussed in the previous chapter, the charging demand of eVTOLs depends on many factors. Current small electric aircraft generally require charging power in the range of several hundred kilowatts. However, as future demand continues to grow, megawatt power levels for charging will eventually become necessary [81]. Meanwhile, the high operational turnover and punctual departure requirements of eVTOLs can lead to multiple aircraft charging within the same time windows, which may create significant spikes at the feeder level and cause issues such as undervoltage and equipment capacity overload. Relevant studies have shown that eVTOL charging requirements can cause the peak load at the charging stations to increase by six to seven times, while the existing systems can only handle two to three times the current demand [7]. Additionally, the aggregated power of vertiports is influenced by flight missions and schedules, with user demand significantly impacting the energy consumption and charging requirements of eVTOLs. Distribution networks therefore face

a highly concentrated transportation load.

B. Distribution Network Planning and Coordinated Operation with eVTOL Charging

To address the capacity and operational challenges caused by eVTOL charging, both vertiport and distribution network measures can be considered. Integrated energy microgrids can reduce vertiport dependence on the external grid by coordinating local generation, energy storage, and flexible loads. This approach has been discussed in Section III-B and is not repeated here. This section focuses on distribution network responses over different time scales. Long-term measures include infrastructure planning and capacity enhancement, while short-term operation can use network reconfiguration and Volt/VAR Control (VVC). When these measures are insufficient, the DSO can further coordinate charging resources and other distributed flexibility.

1) Infrastructure Planning and Capacity Enhancement

Distribution networks in areas with insufficient capacity will require infrastructure expansion and upgrades. Vertiport siting and the internal configuration of charging facilities and energy storage depend on transportation demand, aviation operations, land availability, and investment decisions. These issues are not discussed in this subsection. From the grid perspective, the main task is to determine the location, capacity, and timing of upgrades to feeders, transformers, connection lines, and substations.

Existing UAM studies have examined whether available power capacity can support large-scale aviation electrification at a broad system level. Thipphavong [82] estimated the number of UAM aircraft that could be charged simultaneously in different years based on the available capacity of the three major U.S. interconnections. The study also considered the reduction in remaining capacity caused by the growth of ground EVs. It assumed that electricity could be delivered as needed within each interconnection. It only provides a capacity estimate and does not represent power flow, equipment limits, or local constraints in distribution networks. It is also not suitable for direct investment decisions.

Distribution network expansion studies for EV integration provide useful methodological references. Wang et al. [83] developed a mixed integer nonlinear model for large-scale EV integration. The model determines expansion plans under network operating constraints and represents additional charging demand through multiple demand scenarios. It is suitable when load scenarios are largely known, although the results still depend on the predefined scenarios.

When charging demand grows over time, multistage planning can update investment decisions across different development periods. Tao et al. [84], for example, proposed an adaptive joint planning method for electricity networks and fast charging stations under EV diffusion. The method can reduce the risk of overinvestment caused by one-time expansion. However, it requires credible forecasts of future EV diffusion and regional charging demand.

When future loads are uncertain, Bañol Arias et al. [85] developed a multistage joint expansion model for distribution

systems and EV charging facilities. The network decisions include the construction or reinforcement of substations and lines, together with distributed generation and capacitor allocation. Chance constraints are used to control the risk of insufficient substation capacity and ensure that demand is met at a specified confidence level. A higher confidence level improves robustness but usually increases investment cost. Xiang et al. [86] further proposed a two-stage distributionally robust joint expansion model. Candidate charging system plans are generated through a queuing model. Compared with conventional worst-case approaches, this method can use available data and reduce conservativeness, although it is more complex to formulate and solve.

Ehsan and Yang [87] proposed a multistage planning method using representative scenarios for active distribution network reinforcement. Their model jointly considers the construction or reinforcement of substations and feeders, together with wind, photovoltaic, and capacitor investments. Its main value lies in comparing traditional network reinforcement with active resource investment in terms of long-term cost and supply capability, and in assessing whether distributed resources can defer network expansion.

Overall, these studies provide a methodological basis for distribution network planning under eVTOL integration. The key is to develop vertiport load scenarios, growth paths, and uncertainty descriptions that match the planning horizon.

2) Network Reconfiguration and VVC

Distribution networks can also use network reconfiguration and VVC to improve operating conditions under high-power charging loads. Network reconfiguration changes power flow paths by adjusting switch states and can relieve local overloads by using the spare capacity of neighboring feeders [88]. Its effectiveness is limited by network topology, available feeder capacity, and switching constraints. It is therefore more suitable as a local operational mitigation measure.

VVC further coordinates EV charging equipment with conventional voltage regulation resources. Dutta et al. [89] proposed a dual-stage VVC method. Devices with different response characteristics are coordinated across multiple time scales. Hu et al. [90] used the aggregated reactive power capability of EV chargers for real-time voltage regulation. Wang et al. [91] further coordinated EV active charging power and charger reactive power output.

These methods are also applicable to eVTOL charging integration, but their operating limits need to be reassessed. The active power flexibility of eVTOL is generally lower than that of EV. Compared with direct active power curtailment, reactive power support from charging interfaces may be more suitable for eVTOL applications. However, this capability is limited by converter ratings, thermal constraints, and charging operating conditions. Future research should use vertiport load forecasts to evaluate the effectiveness and control limits of these methods under high-power eVTOL charging.

3) Flexibility Coordination

When network reconfiguration and VVC are insufficient to maintain secure distribution network operation, the distribution system operator (DSO) can further coordinate flexibility from

charging stations and other distributed resources. Unlike internal charging scheduling at a vertiport, the focus here is to identify the adjustment capability that each station can provide and to coordinate this capability across multiple stations and other flexible resources.

An aggregate model of charging resources is first required. If the distribution network directly models the behavior of every vehicle, the model size and computational burden increase rapidly with the number of vehicles. Existing studies therefore convert individual vehicle constraints into station or aggregator feasible power regions. Jian et al. [92] proposed an analytical polytope approximation to characterize the aggregate dispatchable region of large-scale EVs under uncertainty. Lu et al. [93] further applied polytope-based aggregation to day-ahead bi-level scheduling of an active distribution network. Zhang et al. [94] improved the computational efficiency of this approach by developing a fast polytope-based method. Zou et al. [95] further incorporated aggregation and disaggregation into the same framework, allowing the aggregate region to be translated back into individual charging schedules. These methods provide compact representations of large vehicle populations, but the resulting regions are generally estimated before actual operation and may become inaccurate when vehicle availability or charging requirements deviate from their forecasts.

Aggregate models not only reduce computational complexity but also provide a unified interface between charging operators and the DSO. Charging operators do not need to disclose the detailed status of every vehicle. They only need to submit an aggregate power range that remains internally feasible. The DSO can then include this range in power flow, equipment capacity, and security constraints without directly controlling individual vehicles. However, the flexibility calculated by a charging operator does not necessarily represent the flexibility that can be safely used by the grid. Wang et al. [96] therefore evaluated the operating boundaries of EV aggregators together with distribution network constraints before the flexibility was provided to the upper-level system. Its main limitation is that the internal scheduling and rapidly changing operating states of individual stations are represented in less detail. Other coordination methods similarly incorporate distribution network constraints into the flexibility activation process [97]. These studies distinguish the theoretical flexibility of charging resources from the flexibility that can be safely activated by the grid.

After aggregate flexibility is identified, the DSO can activate it through different mechanisms. The most direct approach is to include the aggregate feasible region in distribution network optimization and determine power schedules or adjustment targets for charging stations. For multiple charging stations operated by different entities, distributed coordination can also be adopted [98]. Each station retains its internal vehicle information and scheduling authority, exchanges only aggregate variables with the DSO, and iteratively reaches a coordinated solution that satisfies network constraints. While [98] focuses on distributed coordination between charging stations and the distribution network, [99] further introduces

peer-to-peer energy trading among charging stations, while allocating economic benefits among participants. This allows surplus flexibility at one station to support another, but it also increases dependence on communication, market rules, and accurate flexibility assessment.

Other flexible resources can be included to reduce the adjustment pressure placed on charging loads. Yan and Chen [100] coordinated charging stations with shared energy storage and used distributed optimization to balance the interests of the DSO, charging stations, and the storage operator. Its value depends on storage location, capacity, and service cost. This is particularly relevant to eVTOL charging.

Economic signals provide another way to activate flexibility. Yang et al. [101] used dynamic incentive prices to encourage charging stations to adjust their loads. Qian et al. [102] developed a tri-level demand response framework in which the distribution network designs incentives and available flexibility is enhanced through charging station strategies and EV users' charging choices. Ge et al. [103] used distributed game-theoretic and pricing mechanisms to coordinate multiple participants in coupled energy, transportation, and information networks. Price-based and demand response mechanisms preserve the autonomy of charging operators and users, but their effectiveness depends on participation willingness and price responsiveness.

Flexibility coordination must also account for forecast errors in aggregate regions and actual responses. Uncertainty may cause the available adjustment range to deviate from its day-ahead estimate. In addition to the joint chance-constrained method in [104], distributionally robust optimization can also be used [105]. Chance-constrained methods are suitable when reliable probability information is available, whereas distributionally robust methods are more appropriate when data are limited or the underlying probability distribution is difficult to identify. These methods improve the reliability of day-ahead coordination, but they cannot fully capture changes that occur during operation. To address this problem, Yan et al. [106] used real-time feedback to update aggregate flexibility when actual charging states deviated from earlier estimates. Wang et al. [107] further linked online flexibility estimation with hierarchical coordination. Zhang et al. [108] used a learning framework to accelerate flexibility estimation and real-time command allocation, although its reliability depends on the coverage of the training scenarios. Other learning-based methods, such as offline meta-reinforcement learning, can improve the adaptation of control policies to different regulation tasks [109]. These methods are particularly useful when flexibility changes rapidly and repeated model-based optimization becomes computationally demanding.

These studies provide a basis for coordinating vertiport flexibility in distribution networks, but the aggregate model must be reformulated to reflect aviation operating constraints. Aggregating the feasible regions of individual aircraft can form a dynamic power region at the vertiport level. Moreover, compared with EV charging stations, the aggregate feasible region of a vertiport is generally narrower and changes more rapidly. Flight delays, cancellations, and unscheduled missions

can alter aircraft dwell times and charging requirements. The vertiport should therefore update its feasible region using the latest operational information, while the DSO should revise its power limits and coordination plan accordingly. eVTOL integration also changes the priority of flexible resource activation. The DSO should generally coordinate energy storage, ground EVs, and other flexible resources before adjusting eVTOL charging within the vertiport feasible region. Price mechanisms can still guide ground EVs and other flexible loads. For eVTOL services, pricing may also influence travel demand and flight scheduling over longer time scales. However, this signal must pass through user choice and airline operating decisions before affecting charging demand, making it unsuitable for real-time distribution network regulation.

V. CONCLUSION AND FUTURE RESEARCH DIRECTIONS

This review considers eVTOL charging loads as a multi-scale coupling problem between aerial mobility operations and distribution networks. It emphasizes the importance of charging demand modeling and spatiotemporal forecasting for distribution network planning and active response, and identifies the main priorities for future research.

The first priority is to establish reliable mission-driven charging load models. We believe that microscopic simulation is a feasible approach to this problem. By tracking individual aircraft operations and charging events across multiple vertiports, it can provide a consistent basis for urban load forecasting and grid impact assessment. A coupled simulation platform for ground transportation, low-altitude air traffic, and distribution networks could further support both interaction analysis and the validation of scheduling methods.

It is also necessary to develop intelligent vertiport charging scheduling methods that satisfy both flight mission constraints and distribution network security requirements. eVTOLs, ground EVs, energy storage systems, distributed generation, and local station loads should be coordinated within an integrated energy microgrid.

Finally, a bi-level active scheduling framework should be developed for distribution networks with eVTOL integration. At the upper level, the distribution system operator determines vertiport power limits and adjustment requirements according to power flow, equipment capacity, voltage, and other operating constraints. At the lower level, each vertiport coordinates its internal flexible resources and reports its feasible flexibility to the distribution network. Information exchange and rolling updates between the two levels can coordinate aviation operation requirements with secure distribution network operation.

REFERENCES

- [1] H. D. Kim, A. T. Perry, and P. J. Ansell, "A review of distributed electric propulsion concepts for air vehicle technology," in *Proc. AIAA/IEEE Electr. Aircr. Technol. Symp. (EATS)*, Cincinnati, OH, USA, 2018, pp. 1-21.
- [2] Ministry of Industry and Information Technology of the People's Republic of China, Ministry of Science and Technology of the People's Republic of China, Ministry of Finance of the People's Republic of China, and Civil Aviation Administration of China. (2024, Mar. 27). *General Aviation Equipment Innovation and Application Implementation Plan (2024-2030)*. Beijing, China. [Online]. Available: https://wap.miit.gov.cn/zwgk/zcwj/wjfb/tz/art/2024/art_4ce8d09c15ee4fb1aefc3d5d8bbb6584.html
- [3] Federal Aviation Administration. (2023, Jul. 18). *Advanced Air Mobility (AAM) Implementation Plan, Version 1.0*. U.S. Department of Transportation, Washington, DC, USA. [Online]. Available: <https://www.faa.gov/sites/faa.gov/files/AAM-I28-Implementation-Plan.pdf>
- [4] European Commission. (2022, Nov. 29). *A Drone Strategy 2.0 for a Smart and Sustainable Unmanned Aircraft Eco-System in Europe*. Brussels, Belgium, COM(2022) 652 final. [Online]. Available: https://transport.ec.europa.eu/system/files/2022-11/COM_2022_652_drone_strategy_2.0.pdf
- [5] Department for Transport. (2024, Mar. 18). *Future of Flight Action Plan*. London, U.K. [Online]. Available: <https://assets.publishing.service.gov.uk/media/661943b7679e9c8d921dfee/b/fof-action-plan.pdf>
- [6] X.-G. Yang, T. Liu, S. Ge, E. Rountree, and C.-Y. Wang, "Challenges and key requirements of batteries for electric vertical takeoff and landing aircraft," *Joule*, vol. 5, no. 7, pp. 1644-1659, Jul. 2021.
- [7] P. Paudyal, S. A. Abraham, J. Wang, H. Padullaparti, and B. Solanki, "Study of eVTOL charging impact on airport electrical grids," in *Proc. IEEE PES T&D Conf. Expo.*, Anaheim, CA, USA, 2024, pp. 1-5.
- [8] K. Qian, C. Zhou, M. Allan, and Y. Yuan, "Modeling of load demand due to EV battery charging in distribution systems," *IEEE Trans. Power Syst.*, vol. 26, no. 2, pp. 802-810, May 2011.
- [9] G. Ferro, R. Minciardi, and M. Robba, "A user equilibrium model for electric vehicles: Joint traffic and energy demand assignment," *Energy*, vol. 198, Art. no. 117299, May 2020.
- [10] X. Liao, X. Kang, M. Li, and N. Cao, "Short term load forecasting and early warning of charging station based on PSO-SVM," in *Int. Conf. Intell. Transp., Big Data & Smart City (ICITBS)*, Changsha, China, 2019, pp. 305-308.
- [11] A. Hussain, Q.-C. Lu, S. S. Rizvi, S. Wang, and S. J. Kwon, "Short term demand forecasting of electric vehicle charging stations using context aware temporal transformer model," *Scientific Reports*, vol. 15, no. 1, Art. no. 36652, Oct. 2025.
- [12] T. Zhang, Q. Peng, and S. Zeng, "Predicting EV charging demand in renewable-energy-powered grids using explainable machine learning," *Sustainability*, vol. 17, no. 9, Art. no. 4158, May 2025.
- [13] B. Solanki et al., "Federal aviation administration vertiport electrical infrastructure study," National Renewable Energy Laboratory (NREL), Golden, CO (United States), Tech. Rep. NREL/TP--5R00-86245, Nov. 2023.
- [14] N. Hagag, S. Gasche, F. Jäger, and C. Kallies, "Energy demand analysis for eVTOLs in cluttered and dynamic environments based on adaptive trajectory prediction," in *Proc. Integrated Communications, Navigation and Surveillance Conf. (ICNS)*, Herndon, VA, USA, 2024, pp. 1-15.
- [15] Y. Liang, D. Bodnár, G. Ram Chandra Mouli, D. Ragni, and P. Bauer, "Charging demand prediction: small all-electric aircraft and electric vertical takeoff and landing aircraft," *IEEE Trans. Transp. Electr.*, vol. 11, no. 1, pp. 2732-2747, Feb. 2025.
- [16] A. G. Taye, P. Pradeep, P. Wei, J. C. Jones, T. Bonin, and D. Eberle, "Energy demand analysis for eVTOL charging stations in urban air mobility," in *Proc. AIAA AVIATION Forum and ASCEND*, Las Vegas, NV, USA, 2024, pp. 1-11.
- [17] H. Wei, B. Lou, Z. Zhang, B. Liang, F.-Y. Wang, and C. Lv, "Autonomous navigation for eVTOL: review and future perspectives," *IEEE Trans. Intell. Veh.*, vol. 9, no. 2, pp. 4145-4171, Feb. 2024.
- [18] S. Xiang, A. Xie, M. Ye, X. Yan, X. Han, H. Niu, Q. Li, and H. Huang, "Autonomous eVTOL: a summary of researches and challenges," *Green Energy Intell. Transp.*, vol. 3, no. 1, Art. no. 100140, Feb. 2024.
- [19] J. Su, H. Huang, H. Zhang, Y. Wang, and F.-Y. Wang, "eVTOL performance analysis: a review from control perspectives," *IEEE Trans. Intell. Veh.*, vol. 9, no. 5, pp. 4877-4889, May 2024.
- [20] E. Thompson et al., "A survey of eVTOL aircraft and AAM operation hazards," in *Proc. AIAA AVIATION Forum*, Chicago, IL, USA, 2022, Paper AIAA 2022-3539.
- [21] W. Raza and R. S. Stansbury, "Noise prediction and mitigation for UAS and eVTOL aircraft: a survey," *Drones*, vol. 9, no. 8, pp. 577-610, Aug. 2025.
- [22] Z. Li, P. Xie, C. Lin, and G. Liu, "A state-of-the-art review on eVTOL thermal management: system architectures, key components and emerging technologies," *eTransportation*, vol. 26, Art. no. 100480, Dec. 2025.

- [23] B. Wang, T. Xu, B. Zheng, Y. Kai, and K. Zhang, "Predicting battery degradation for electric vertical take-off and landing (eVTOL) aircraft: a comprehensive review of methods, challenges, and future trends," *eTransportation*, vol. 26, Art. no. 100477, Dec. 2025.
- [24] F. Yu et al., "A review of hybrid-electric propulsion in aviation: modeling methods, energy management strategies, and future prospects," *Aerospace*, vol. 12, no. 10, Art. no. 895, Oct. 2025.
- [25] W. Johnson and C. Silva, "NASA concept vehicles and the engineering of advanced air mobility aircraft," *Aeronaut. J.*, vol. 126, no. 1295, pp. 59–91, Jan. 2022.
- [26] A. R. Kadhiresan and M. J. Duffy, "Conceptual design and mission analysis for eVTOL urban air mobility flight vehicle configurations," in *Proc. AIAA Aviation Forum*, Dallas, TX, USA, 2019, Paper AIAA 2019-2873.
- [27] W. Johnson, C. Silva, and E. Solis, "Concept vehicles for VTOL air taxi operations," in *Proc. AHS Specialists' Conf. Aeromechanics Design for Transformative Vertical Flight*, San Francisco, CA, USA, 2018.
- [28] "eVTOL classifications." Accessed: Jul. 12, 2026. [Online]. Available: <https://evtol.news/classifications>
- [29] Y. Yang et al., "Sizing of multicopter air taxis—weight, endurance, and range," *Aerospace*, vol. 11, no. 3, Art. no. 200, Mar. 2024.
- [30] A. Bacchini and E. Cestino, "Electric VTOL configurations comparison," *Aerospace*, vol. 6, no. 3, Art. no. 26, Feb. 2019.
- [31] O. Ugwueze, T. Statheros, N. Horri, M. Innocente, and M. Bromfield, "Investigation of a mission-based sizing method for electric VTOL aircraft preliminary design," in *Proc. AIAA SciTech Forum*, San Diego, CA, USA, 2022, Paper AIAA 2022-1931.
- [32] O. Ugwueze, T. Statheros, N. Horri, M. A. Bromfield, and J. Simo, "An efficient and robust sizing method for eVTOL aircraft configurations in conceptual design," *Aerospace*, vol. 10, no. 3, Art. no. 311, Mar. 2023.
- [33] A. Kasliwal et al., "Role of flying cars in sustainable mobility," *Nat. Commun.*, vol. 10, no. 1, Art. no. 1555, Apr. 2019.
- [34] Y. Ayalew, W. Bedada, A. Homaifar, and K. Freeman, "Data driven UAM flight energy consumption prediction and risk assessment," presented at Intelligent Systems with Applications (ISWA), Virtual, Feb. 10, 2023. [Online]. Available: <https://ntrs.nasa.gov/citations/20220019058>
- [35] U.S. Code of Federal Regulations, "IFR: Alternate airport requirements," 14 CFR § 135.223. [Online]. Available: <https://www.ecfr.gov/current/title-14/chapter-I/subchapter-G/part-135/subpart-D/section-135.223>
- [36] Uber. (Oct. 27, 2016). Uber Elevate: Fast-Forwarding to a Future of On-Demand Urban Air Transportation. [Online]. Available: https://d1n9ezh1ys8wfo.cloudfront.net/static/PDFs/Elevate%2BWhitepaper.pdf?uclid_id=4e6d76ac-7c01-42ea-948c-ef4839e8345d
- [37] Uber. (Oct. 27, 2016). Uber Air Vehicle Requirements and Missions. [Online]. Available: <https://s3.amazonaws.com/uber-static/elevate/Summary+Mission+and+Requirements.pdf>
- [38] S. P. Melo, F. Cerdas, A. Barke, C. Thies, T. S. Spengler, and C. Herrmann, "Life cycle engineering of future aircraft systems: the case of eVTOL vehicles," *Procedia CIRP*, vol. 90, pp. 297–302, 2020.
- [39] C. Zammit and E.-J. van Kampen, "Comparison between a* and RRT algorithms for 3D UAV path planning," *Unmanned Syst.*, vol. 10, no. 2, pp. 129–146, Oct. 2021.
- [40] S. Koenig, M. Likhachev, and D. Furcy, "Lifelong planning a*," *Artif. Intell.*, vol. 155, no. 1–2, pp. 93–146, May 2004.
- [41] X. Xu, F. Zhang, and Y. Zhao, "Unmanned aerial vehicle path-planning method based on improved P-RRT* algorithm," *Electronics*, vol. 12, no. 22, Art. no. 4576, Nov. 2023.
- [42] S. Karaman and E. Frazzoli, "Sampling-based algorithms for optimal motion planning," *Int. J. Rob. Res.*, vol. 30, no. 7, pp. 846–894, Jun. 2011.
- [43] A. Sonmez, E. Kocyigit, and E. Kugu, "Optimal path planning for UAVs using genetic algorithm," in *Proc. Int. Conf. Unmanned Aircraft Syst. (ICUAS)*, Denver, CO, USA, 2015, pp. 50–55.
- [44] Y. Liu, H. Zhang, H. Zheng, Q. Li, and Q. Tian, "A spherical vector-based adaptive evolutionary particle swarm optimization for UAV path planning under threat conditions," *Sci. Rep.*, vol. 15, no. 1, Art. no. 2116, Jan. 2025.
- [45] L. Wang, H. Wang, X. Yang, Y. Gao, X. Cui, and B. Wang, "Research on smooth path planning method based on improved ant colony algorithm optimized by floyd algorithm," *Front. Neurobot.*, vol. 16, Art. no. 955179, Aug. 2022.
- [46] B. Abhishek, S. Ranjit, T. Shankar, G. Eappen, P. Sivasankar, and A. Rajesh, "Hybrid PSO-HSA and PSO-GA algorithm for 3D path planning in autonomous UAVs," *SN Appl. Sci.*, vol. 2, Art. no. 1805, Oct. 2020.
- [47] Y. Zhou, L. Yan, Y. Han, H. Xie, and Y. Zhao, "A survey on the key technologies of UAV motion planning," *Drones*, vol. 9, no. 3, Art. no. 194, Mar. 2025.
- [48] D. Mellinger and V. Kumar, "Minimum snap trajectory generation and control for quadrotors," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, Shanghai, China, 2011, pp. 2520–2525.
- [49] J. Chen, T. Liu, and S. Shen, "Online generation of collision-free trajectories for quadrotor flight in unknown cluttered environments," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, Stockholm, Sweden, 2016, pp. 1476–1483.
- [50] J. Sun, G. Xu, Z. Wang, T. Long, and J. Sun, "Safe flight corridor constrained sequential convex programming for efficient trajectory generation of fixed-wing UAVs," *Chin. J. Aeronaut.*, vol. 38, no. 1, Art. no. 103174, Jan. 2025.
- [51] N. Ratliff, M. Zucker, J. A. Bagnell, and S. Srinivasa, "CHOMP: gradient optimization techniques for efficient motion planning," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, Kobe, Japan, 2009, pp. 489–494.
- [52] M. Kalakrishnan, S. Chitta, E. Theodorou, P. Pastor, and S. Schaal, "STOMP: stochastic trajectory optimization for motion planning," in *Proc. IEEE Int. Conf. Robot. Autom. (ICRA)*, Shanghai, China, 2011, pp. 4569–4574.
- [53] H. Oleynikova, M. Burri, Z. Taylor, J. Nieto, R. Siegwart, and E. Galceran, "Continuous-time trajectory optimization for online UAV replanning," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Daejeon, South Korea, 2016, pp. 5332–5339.
- [54] W. Sun, P. Sun, W. Ding, J. Zhao, and Y. Li, "Gradient-based autonomous obstacle avoidance trajectory planning for B-spline UAVs," *Sci. Rep.*, vol. 14, no. 1, Art. no. 14458, Jun. 2024.
- [55] Y. Xie, Z. Song, R. Yang, Y. Qian, M. Yu, H. Li, and Y. Zhang, "An Improved Velocity Planning Method for eVTOL Aircraft Based on Differential Evolution Algorithm Considering Flight Economy," *IEEE Trans. Transp. Electrific.*, vol. 11, no. 1, pp. 3980–3995, Feb. 2025.
- [56] N. Kang, L. Lu, and J. Whidborne, "Energy optimization strategies for automatic tiltrotor electric vertical takeoff and landing aircraft," *J. Guid. Control Dyn.*, vol. 48, no. 5, pp. 1196–1200, 2025.
- [57] Y. Li and M. Liu, "Path planning of electric VTOL UAV considering minimum energy consumption in urban areas," *Sustainability*, vol. 14, no. 20, Art. no. 13421, Oct. 2022.
- [58] P. Pradeep, G. B. Chatterji, B. Sridhar, K.-M. Edholm, T. A. Lauderdale, K. Sheth, C.-F. Lai, and H. Erzberger, "Wind-optimal trajectories for multirotor eVTOL aircraft on UAM missions," presented at AIAA Aviation Forum, Virtual, Jun. 15–19, 2020. [Online]. Available: <https://ntrs.nasa.gov/citations/20205002518>
- [59] M. Wang, S. O. D. Luiz, S. Zhang, and A. M. N. Lima, "Electric flight in extreme and uncertain urban environments," *Sustainability*, vol. 15, no. 16, Art. no. 12590, Aug. 2023.
- [60] A. Bills, S. Sripad, L. Fredericks, M. Guttenberg, D. Charles, E. Frank, and V. Viswanathan, "A battery dataset for electric vertical takeoff and landing aircraft," *Sci. Data*, vol. 10, no. 1, Art. no. 344, Jun. 2023.
- [61] M. Mitici, B. Hennink, M. Pavel, and J. Dong, "Prognostics for lithium-ion batteries for electric vertical take-off and landing aircraft using data-driven machine learning," *Energy AI*, vol. 12, Art. no. 100233, Apr. 2023.
- [62] K. Liu, C. Zou, K. Li, and T. Wik, "Charging pattern optimization for lithium-ion batteries with an electrothermal-aging model," *IEEE Trans. Ind. Informat.*, vol. 14, no. 12, pp. 5463–5474, Dec. 2018.
- [63] G.-J. Chen and W.-H. Chung, "Evaluation of charging methods for lithium-ion batteries," *Electronics*, vol. 12, no. 19, Art. no. 4095, Sep. 2023.
- [64] Z. Wu and Y. Zhang, "Optimal eVTOL charging and passenger serving scheduling for on-demand urban air mobility," in *Proc. AIAA Aviation Forum*, 2020, Paper AIAA 2020-3253.
- [65] J. Yue, T. Qian, Q. Hu, and H. Hui, "Consumer-facing low-altitude urban air mobility: energy-constrained service commitment and trustworthy access," *IEEE Trans. Consum. Electron.*, early access, 2026.
- [66] I. C. Kleinbekman, M. Mitici, and P. Wei, "Rolling-horizon electric vertical takeoff and landing arrival scheduling for on-demand urban air mobility," *J. Aerosp. Inf. Syst.*, vol. 17, no. 3, pp. 150–159, Mar. 2020.
- [67] H. Shon and J. Lee, "An optimization framework for urban air mobility (UAM) planning and operations," *J. Air Transp. Manage.*, vol. 124, Art. no. 102720, Apr. 2025.
- [68] J. Wu, S. Cao, M. Hansen, and M. C. González, "Integrating urban air mobility into the power grid through smart charging solutions," *Transp. Res. Part C Emerging Technol.*, vol. 179, Art. no. 105281, Oct. 2025.
- [69] Z. Guo, X. Zhang, and R. Zhang, "A multi-agent microgrid energy management solution for air transport electrification," in *Proc. 10th Renewable Power Generation Conf. (RPG 2021)*, Oct. 2021, pp. 318–324.
- [70] Z. Liu, B. Borlaug, A. Meintz, C. Neuman, E. Wood, and J. Bennett, "Data-driven method for electric vehicle charging demand analysis: case

- study in virginia,” *Transp. Res. Part D Transp. Environ.*, vol. 125, Art. no. 103994, Dec. 2023.
- [71] L. Zhang, Z. Huang, Z. Wang, X. Li, and F. Sun, “An urban charging load forecasting model based on trip chain model for private passenger electric vehicles: a case study in Beijing,” *Energy*, vol. 299, Art. no. 130844, Jul. 2024.
- [72] T. Qian, M. Fang, Q. Hu, C. Shao, and J. Zheng, “V2Sim: an open-source microscopic V2G simulation platform in urban power and transportation network,” *IEEE Trans. Smart Grid*, vol. 16, no. 4, pp. 3167–3178, Jul. 2025.
- [73] T. Qian, B. Yuan, Z. Liang, Q. Hu, C. Shao, and Z. Wu, “Coordinated EV OD demand estimation and traffic sensor placement in smart grid and intelligent transportation system,” *IEEE Trans. Transp. Electrific.*, early access, 2026.
- [74] Y. Huang and K. M. Kockelman, “Electric vehicle charging station locations: elastic demand, station congestion, and network equilibrium,” *Transp. Res. Part D Transp. Environ.*, vol. 78, Art. no. 102179, Jan. 2020.
- [75] K. Liu and Y. Liu, “Stochastic user equilibrium based spatial-temporal distribution prediction of electric vehicle charging load,” *Appl. Energy*, vol. 339, Art. no. 120943, Jun. 2023.
- [76] S. Tang, Y. Mu, X. Dong, H. Jia, and X. Yu, “Modeling electric vehicle charging load dynamics: a spatial-temporal approach integrating trip chains and dynamic user equilibrium,” *IEEE Trans. Smart Grid*, vol. 16, no. 1, pp. 582–597, Jan. 2025.
- [77] Z. Liang et al., “A strategic EV charging networks planning framework for intercity highway with time-expanded user equilibrium,” *IEEE Trans. Smart Grid*, vol. 16, no. 6, pp. 5215–5229, Nov. 2025.
- [78] S. Wang, A. Chen, P. Wang, and C. Zhuge, “Predicting electric vehicle charging demand using a heterogeneous spatio-temporal graph convolutional network,” *Transp. Res. Part C Emerging Technol.*, vol. 153, Art. no. 104205, Aug. 2023.
- [79] H. Kuang, H. Qu, K. Deng, and J. Li, “A physics-informed graph learning approach for citywide electric vehicle charging demand prediction and pricing,” *Appl. Energy*, vol. 363, Art. no. 123059, Jun. 2024.
- [80] T. Qian, J. Yue, C. Wang, J. Li, Q. Hu, and H. Hui, “Urban energy and three-dimensional mobility integration for eVTOL scale-up,” *Appl. Energy*, vol. 421, Art. no. 128226, 2026.
- [81] Y. Liang, G. R. C. Mouli, and P. Bauer, “Charging technology for electric aircraft: state of the art, trends, and challenges,” *IEEE Trans. Transp. Electrific.*, vol. 10, no. 3, pp. 6761–6788, Sep. 2024.
- [82] D. P. Thipphavong, “Analysis of electrical grid capacity by interconnection for urban air mobility,” in *Proc. AIAA AVIATION Forum*, Chicago, IL, USA, Jun. 2022, Paper AIAA 2022-3316.
- [83] S. Wang, Z. Y. Dong, F. Luo, K. Meng, and Y. Zhang, “Stochastic collaborative planning of electric vehicle charging stations and power distribution system,” *IEEE Trans. Ind. Informat.*, vol. 14, no. 1, pp. 321–331, Jan. 2018.
- [84] Y. Tao, J. Qiu, S. Lai, X. Sun, and J. Zhao, “Adaptive integrated planning of electricity networks and fast charging stations under electric vehicle diffusion,” *IEEE Trans. Power Syst.*, vol. 38, no. 1, pp. 499–513, Jan. 2023.
- [85] N. Bañol Arias, A. Tabares, J. F. Franco, M. Lavorato, and R. Romero, “Robust joint expansion planning of electrical distribution systems and EV charging stations,” *IEEE Trans. Sustain. Energy*, vol. 9, no. 2, pp. 884–894, Apr. 2018.
- [86] Y. Xiang et al., “Robust expansion planning of electric vehicle charging system and distribution networks,” *CSEE J. Power Energy Syst.*, vol. 10, no. 6, pp. 2457–2469, Nov. 2024.
- [87] A. Ehsan and Q. Yang, “Active distribution system reinforcement planning with EV charging stations—part I: uncertainty modeling and problem formulation,” *IEEE Trans. Sustain. Energy*, vol. 11, no. 2, pp. 970–978, Apr. 2020.
- [88] X. Jin, T. Yu, X. Wang, S. Li, and T. Pu, “A reconfiguration strategy for active distribution network with electric vehicles,” in *Proc. 2016 Int. Conf. Smart Grid Clean Energy Technol. (ICSGCE)*, Oct. 2016, pp. 155–160.
- [89] A. Dutta, S. Ganguly, and C. Kumar, “Coordinated volt/var control of PV and EV interfaced active distribution networks based on dual-stage model predictive control,” *IEEE Syst. J.*, vol. 16, no. 3, pp. 4291–4300, Sep. 2022.
- [90] J. Hu, C. Ye, Y. Ding, J. Tang, and S. Liu, “A distributed MPC to exploit reactive power V2G for real-time voltage regulation in distribution networks,” *IEEE Trans. Smart Grid*, vol. 13, no. 1, pp. 576–588, Jan. 2022.
- [91] J. Wang, G. R. Bharati, S. Paudyal, O. Ceylan, B. P. Bhattarai, and K. S. Myers, “Coordinated electric vehicle charging with reactive power support to distribution grids,” *IEEE Trans. Ind. Informat.*, vol. 15, no. 1, pp. 54–63, Jan. 2019.
- [92] J. Jian, M. Zhang, Y. Xu, W. Tang, and S. He, “An analytical polytope approximation aggregation of electric vehicles considering uncertainty for the day-ahead distribution network dispatching,” *IEEE Trans. Sustain. Energy*, vol. 15, no. 1, pp. 160–172, Jan. 2024, doi: 10.1109/TSTE.2023.3275566.
- [93] J. Lu, J. Zhu, R. Zhao, W. Guo, Y. Xu, and C. Lin, “Polytope-based aggregation of electric vehicles for day-ahead bi-level scheduling of active distribution network considering uncertainties,” in *Proc. 2024 7th International Conference on Energy, Electrical and Power Engineering (CEEPE)*, 2024, pp. 808–812.
- [94] M. Zhang, Y. Xu, X. Shi, and Q. Guo, “A fast polytope-based approach for aggregating large-scale electric vehicles in the joint market under uncertainty,” *IEEE Trans. Smart Grid*, vol. 15, no. 1, pp. 701–713, Jan. 2024.
- [95] H. Zou, W. Gao, Y. Zhang, J. Xia, and Z.-W. Liu, “Polytope-based flexible aggregation and disaggregation strategy for electric vehicles,” in *2025 IEEE International Conference on Industrial Technology (ICIT)*, Mar. 2025, pp. 1–6.
- [96] L. Wang, J. Kwon, N. Schulz, and Z. Zhou, “Evaluation of aggregated EV flexibility with TSO-DSO coordination,” *IEEE Trans. Sustain. Energy*, vol. 13, no. 4, pp. 2304–2315, Oct. 2022.
- [97] M. M. Hoque, M. Khorasany, R. Razzaghi, M. Jalili, and H. Wang, “Network-aware coordination of aggregated electric vehicles considering charge-discharge flexibility,” *IEEE Trans. Smart Grid*, vol. 14, no. 3, pp. 2125–2139, May 2023.
- [98] D. Yan, C. Ma, and Y. Chen, “Distributed coordination of charging stations considering aggregate EV power flexibility,” *IEEE Trans. Sustain. Energy*, vol. 14, no. 1, pp. 356–370, Jan. 2023.
- [99] J. Zhang, L. Che, X. Wan, and M. Shahidehpour, “Distributed hierarchical coordination of networked charging stations based on peer-to-peer trading and EV charging flexibility quantification,” *IEEE Trans. Power Syst.*, vol. 37, no. 4, pp. 2961–2975, Jul. 2022.
- [100] D. Yan and Y. Chen, “Distributed coordination of charging stations with shared energy storage in a distribution network,” *IEEE Trans. Smart Grid*, vol. 14, no. 6, pp. 4666–4682, Nov. 2023.
- [101] H. Yang, Y. Xu, and Q. Guo, “Dynamic incentive pricing on charging stations for real-time congestion management in distribution network: An adaptive model-based safe deep reinforcement learning method,” *IEEE Trans. Sustain. Energy*, vol. 15, no. 2, pp. 1100–1113, Apr. 2024.
- [102] T. Qian, Z. Liang, S. Chen, Q. Hu, and Z. Wu, “A tri-level demand response framework for EVCS flexibility enhancement in coupled power and transportation networks,” *IEEE Trans. Smart Grid*, vol. 16, no. 1, pp. 598–611, Jan. 2025.
- [103] X. Ge, G. Wang, R. Sun, and F. Wang, “A distributed and game-theoretic-based EV charging pricing model under coupled energy-transportation-information networks,” *IEEE Trans. Smart Grid*, vol. 16, no. 1, pp. 297–310, Jan. 2025.
- [104] J. Zhu, Y. Xu, and H. Sun, “Day-ahead joint chance-constrained optimal scheduling of the distribution network with electric vehicle aggregators,” *IEEE Trans. Smart Grid*, vol. 16, no. 6, pp. 5311–5323, Nov. 2025.
- [105] X. Shi, Y. Xu, Q. Guo, H. Sun, and X. Zhang, “Day-ahead distributionally robust optimization-based scheduling for distribution systems with electric vehicles,” *IEEE Trans. Smart Grid*, vol. 14, no. 4, pp. 2837–2850, Jul. 2023.
- [106] D. Yan, S. Huang, and Y. Chen, “Real-time feedback based online aggregate EV power flexibility characterization,” *IEEE Trans. Sustain. Energy*, vol. 15, no. 1, pp. 658–673, Jan. 2024.
- [107] X. Wang, S. Wang, L. Du, and Y. Chen, “Online hierarchical aggregate power flexibility characterization of EV charging stations with disaggregation feasibility guarantee,” *IEEE Trans. Transp. Electrific.*, vol. 11, no. 6, pp. 13274–13286, Dec. 2025.
- [108] M. Zhang, H. Yang, Y. Xu, and H. Sun, “Learning-based real-time aggregate flexibility provision and scheduling of electric vehicles,” *IEEE Trans. Smart Grid*, vol. 15, no. 6, pp. 5840–5852, Nov. 2024.
- [109] Z. Liang et al., “LLM-enhanced offline meta-reinforcement learning for multi-task V2G regulation: a human-AI collaborative framework,” *IEEE Trans. Smart Grid*, early access, 2026.