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Development of a generalized eVTOL vehicle cost model for Urban Air Mobility operations☆

Ansgar Kirste *, Eike Stumpf

Institute of Aerospace Systems, RWTH Aachen University, Wuellnerstrasse 7, Aachen, 52062, Germany

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ABSTRACT

The market potential for profitable operations of electric vertical take-off and landing (eVTOL) vehicles within Urban Air Mobility (UAM) depends mainly on total costs, including investments in infrastructure, eVTOL vehicle production, and air traffic management. Total cost models including vehicle production from the manufacturer's perspective and operating systems on fleet level are required to comprehensively analyze feasible UAM operations. This paper models eVTOL concept-specific costs within a generalized Total Cost of Ownership estimation combining operational demand simulation and extended eVTOL data. The model incorporates approaches of DAPCA IV with extensions for eVTOL vehicles and divides production costs into airframe, avionics, and propulsion. Parameterization is carried out through literature review of previous cost models and reference data. Revenue is derived from agent-based demand simulation instances utilizing MATSim. Results are carried out for eleven eVTOL vehicles, including five Lift + Cruise, three Tilt-Rotor, one Tilt-Wing, and two Multicopter concepts. In the metropolitan region Rhine–Ruhr, autonomous flight operations are required for cost-efficient operations, high production volumes are beneficial, and optimized ticket price ranges average two euros per kilometer. Sensitivities for a near-term scenario indicate the relevance of investments in infrastructure and ramp-up strategies for manufacturers, as profit margins are rather small, and some eVTOL concepts are cost-inefficient. Based on this work, the detailed cost estimation tool can be applied to evaluate feasible UAM operations in future research scenarios accounting for previous parameter uncertainties. Parametric vehicle design optimization can be advanced considering cost couplings between vehicle level and fleet level.

1. Introduction

Recent developments in vehicle concepts and continuous progress in certification make Urban Air Mobility (UAM) increasingly realistic (Babetto et al., 2023; Kiesewetter et al., 2023). To support investment decisions and strategic planning of potential operators and policymakers, accurate cost estimation is critical for UAM success. Manufacturers need to optimize vehicle designs for cost-competitiveness given several scenario developments, while meeting safety and certification requirements. Without robust cost modeling frameworks, these stakeholders cannot make evidence-based decisions. At vehicle level, electric vertical take-off and landing (eVTOL) vehicles have been designed with regard to safety aspects while also minimizing rotor noise emissions for improved acceptance and sustainability (Afonso et al., 2021; André, 2022; Rizzi et al., 2020). Battery technology development is critical for feasibility, and in much of the recent research, a battery-specific energy density of around 400 Wh/kg has been forecasted by 2030 and identified as a relevant factor for a broader implementation of UAM services within various scenarios (Kiesewetter et al., 2023). These services comprise generally airport shuttles, intra-city and inter-city connections, and an implementation on network level combining several UAM trip distances. The latter raises the need to take fleet costs and station planning into account, which means a long planning horizon and a large investment from the potential UAM operator's perspective (Rajendran & Srinivas, 2020).

To now enable cost-efficient operations for large-scale applications, cost optimization approaches are needed (Garrow et al., 2021; Kirste & Stumpf, 2024). In recent research, optimization approaches have been addressed in three categories:

- Deriving mission requirements for initial eVTOL vehicle sizing, e.g. Kirste and Stumpf (2025) and Patterson et al. (2018),

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* Corresponding author.
E-mail addresses: kirste@ilr.rwth-aachen.de, research@ilr.rwth-aachen.de (A. Kirste).

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- Designing and optimizing eVTOL concepts within given design requirements, e.g. Brown and Harris (2018, 2020) and Howard et al. (2021),
- Modeling of eVTOL vehicle fleets within overall mobility networks, e.g. Balac et al. (2019), Kirste and Stumpf (2023) and Rothfeld (2021).

In all these categories a detailed eVTOL vehicle cost modeling is needed. In comprehensive UAM system cost modeling, the Total Cost of Ownership (TCO) approach can be used to categorize costs into infrastructure costs, energy consumption and recharging costs, eVTOL vehicle fleet costs including maintenance, and additional costs (Husemann et al., 2024; Kirste et al., 2023; Mihara et al., 2021). Considering these costs, the UAM market potential has so far been modeled on the basis of specific eVTOL vehicle designs. Here, the performance data of several flight segment's energy consumption are partially supported by experimental studies with a generally high level of detail (Bacchini & Cestino, 2019). While these studies provide valuable foundations for evaluating UAM cost-efficiency, they primarily focus on specific vehicle designs rather than enabling systematic comparison across different eVTOL configurations. These approaches were suitable for early UAM research but becomes limiting given several scenario and technology developments in the near future.

With UAM being near to implementation in areas with governmental and financial support, three methodological limitations in current cost modeling approaches are relevant. First, many studies present time horizon dependent cost developments without providing eVTOL vehicle configuration specifications and optimization (Holden & Goel, 2016). Second, simplified mass-dependent cost factors are used without considering learning effects and configuration-specific requirements that differ between Multicopter, Lift + Cruise, and Tilt-X designs (Brown & Harris, 2018; Husemann et al., 2024). Third, constant demand is often assumed, lacking dependency on ticket pricing and eVTOL vehicle performance parameters such as different cruise speeds.

Building upon previous research contributions, this paper aims to develop a generalized eVTOL vehicle cost model combining eVTOL production costs and UAM fleet level costs. It is further aimed that the following aspects can be analyzed and addressed in subsequent research:

1. to supply a more precise TCO modeling for the purpose of feasibility analysis regarding the overall UAM fleet level,
2. to enable comparability between previous studies and different eVTOL concepts, so that a consistent calculation basis can be used,
3. to model interactions between eVTOL vehicle level and UAM fleet level and thus enable deriving future cost-efficient eVTOL designs from overall system analyses.

2. Literature review

In order to develop both a generalized and detailed cost modeling of eVTOL vehicle concepts, recent literature is analyzed regarding the following sub-criteria:

(1) **eVTOL vehicle design** – The intended cost model should be based on electric aircraft with vertical take-off and landing capabilities.
(2) **Generalized configurational aspects** – The cost model should be applicable for several eVTOL configurations, namely Lift + Cruise, Tilt–Wing, Tilt–Rotor, Vectored Thrust, and Multicopter.
(3) **Mass dependencies** – A dependency of the costs in relation to the empty mass or maximum take-off mass should be included. This is relevant as different eVTOL concepts within a configuration class are associated with different production costs due to their size.

Table 1
Considered study requirements in related eVTOL research.

Requirement	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Holden and Goel (2016)	✓	–	–	✓	✓	✓	–
Duffy et al. (2017)	✓	–	✓	–	✓	–	–
Brown and Harris (2018)	✓	–	✓	–	✓	✓	–
Goyal et al. (2018)	✓	–	✓	–	✓	–	–
Kohlman et al. (2019)	✓	–	✓	–	✓	–	–
Ploetner et al. (2020)	✓	–	–	–	✓	–	✓
Brown and Harris (2020)	✓	–	✓	–	✓	✓	–
Michelmann et al. (2020)	✓	–	–	✓	–	–	–
Mihara et al. (2021)	✓	(✓)	✓	✓	✓	–	–
Kim and Yee (2021)	✓	–	✓	✓	(✓)	–	–
Kirste et al. (2023)	✓	–	✓	–	✓	–	✓
Husemann et al. (2024)	✓	–	✓	–	✓	–	✓
Kirste and Stumpf (2024)	✓	–	✓	–	✓	–	✓
Kirste and Stumpf (2025)	✓	(✓)	✓	–	✓	–	✓
Boren (1967)	–	✓	✓	✓	–	–	–
Blackwell and Eastlake (2000)	–	✓	✓	✓	–	–	–
Curran et al. (2006)	–	–	✓	✓	–	–	–
Gudmundsson (2014)	–	✓	✓	✓	–	–	–
Hoelzen et al. (2018)	–	–	✓	–	✓	–	–
Finger et al. (2019)	–	✓	✓	✓	✓	–	–

Requirements: (1) eVTOL vehicle design, (2) Generalized configurational aspects, (3) Mass dependencies, (4) Learning effects, (5) Battery costs, (6) Autonomy costs, (7) Concept specific flight operations.

(4) **Learning effects** – The model should allow for learning effects considering the vehicle production volume.
(5) **Battery costs** – The cost model includes battery costs that are related to the production time period.
(6) **Autonomy costs** – The intended model should be applicable to eVTOL vehicles for autonomous UAM flight operations and hence include avionic costs for autonomy.
(7) **Concept specific flight operations** – Within the overall cost model, operational aspects within mobility networks are considered. This includes scenario-specific demand modeling based on the performance of the eVTOL vehicles.

Table 1 shows the summary of corresponding relevant recent literature addressing the listed research criteria (1) to (7). It should be noted that there are also other total cost approaches, albeit referring to one of the approaches listed here. In UAM cost modeling, most approaches are fundamentally based either on a linear correlation between vehicle mass and costs as a top-down model or on a model with learning effects and unit numbers as a parametric model. Brown and Harris (2020), Duffy et al. (2017) and Goyal et al. (2018) use the linear approach correlating to the empty mass of the vehicle, so that battery costs can be added with the current available data. In particular, a factor of $ 1102/kg empty mass is used. It should be noted that a factor of $ 770/kg has been used based on assumptions with several reference vehicles (Brown & Harris, 2018). These reference data are subject to bias as costs are compared with different learning effects and quantities. In following publications by Kohlman et al. (2019), a factor for the cost correlation with the maximum take-off mass is assumed, that is $ 333/kg which equals on average $ 650/kg empty mass without battery. To analyze different eVTOL vehicle concepts within a UAM fleet operation, Babetto et al. (2023), Husemann et al. (2024) and Kirste et al. (2023) adopt the approach of an empty mass-specific factor so that biases based on different passenger capacities are avoided.

Publication by Holden and Goel (2016), which estimate costs on the basis of the Quantity Discount Factor (QDF), use cost estimates from the automotive and conventional aviation industries as reference. Differences between several eVTOL vehicle concepts are neglected. Michelmann et al. (2020) estimate the vehicle costs for three different scenario developments as a proportion of the total costs. Kim and Yee (2021) utilize a production volume-dependent approach based on representative eVTOL vehicles and compare initial and near-term

results with studies by Holden and Goel (2016). Mihara et al. (2021) extend these approaches by introducing a combination of top-down, bottom-up and parametric approaches. In particular, engine costs for different configurations are modeled using a top-down approach, battery costs are modeled using a bottom-up approach, and airframe costs are modeled parametrically. Vehicle configurations are differentiated between propeller and ducted configurations.

In aviation, acquisition costs are modeled either data-based, algorithmically or fractionally, depending on the stage of the development process (Shahriar et al., 2022). The data-based approach is exemplified by the work of Curran et al. (2006) whereby a transfer to eVTOL vehicle production would require a large database. The reference model for many studies is the DAPCA (Development and Procurement Costs of Aircraft) model, which is based on an algorithmic approach and requires less data (Blackwell & Eastlake, 2000; Boren, 1967). This model is the basis for relevant extensions, although a direct transfer to eVTOL cost modeling is currently lacking (see Table 1). In particular, aspects of operational demand specifications, autonomy and parameter scaling are lacking for the complete cost modeling of state-of-the-art eVTOL vehicles.

3. Methodology

For detailed eVTOL vehicle cost modeling, the data available in recent publications on relevant cost shares on the one hand and eVTOL performance parameters on the other are used. The DAPCA IV model is used as the reference model, as this allows a minimum of biases due to linearizations (see Section 2). Regarding the DAPCA IV model,

- extensions by Blackwell and Eastlake (2000) for small aircraft,
- consumer price index (CPI) and labor cost rate adjustments by Gudmundsson (2014),
- and extensions by Finger et al. (2019) for electrically powered aircraft,

are considered. Consequently, the mass of the airframe structure and dependencies on flight speed and the number of units in a production period of five years are included by default. To ensure model adaptability for eVTOL vehicles, cost updates and in particular propulsion and avionic costs have to be integrated accordingly. The TCO model at fleet level is modeled subsequently.

The qualitative approach is described in Section 3.1, the overall model is noted in Section 3.2, and operational fleet level costs are specified in Section 3.2.5.

3.1. Approach

The methodological approach is shown in Fig. 1: First, parameter adjustments and model extensions are applied to the DAPCA IV reference model for precise eVTOL acquisition cost modeling. This specifically includes modeling the costs of propulsion and avionics system regarding the Quantity Discount Factor (QDF) as an increase in production volume reduces unit-specific costs through learning effects and economies of scale. Also, the ratio of structural airframe mass to empty mass for the different eVTOL vehicle configurations is detailed. Second, operational cost parameters are included that focus on several cost proportions of recent research, such as battery, energy, recharging, maintenance, infrastructure, and pilot crew costs (Kirste et al., 2023). It should be noted that battery costs are associated with operational costs on eVTOL fleet level as battery cycles and battery mass optimization are energy consumption specific and therefore depend on the overall operational UAM scenario. For final convergence and feasibility assessment on fleet level, price loops between case study scenario and overall cost model are analyzed by optimizing profitability based on revenue and costs. The model is qualitatively applicable to all UAM scenarios and provides comparability for future UAM studies due to the top-down and parametrically modeled cost shares.

3.2. Model

The total acquisition costs of an eVTOL vehicle k without batteries are the sum of airframe, propulsion, and avionic costs (see Eq. (1)). With the latest parameterization of the DAPCA IV model being in 2012 by Gudmundsson (2014), the factor f^{CPI} is the additional Customer Price Index (CPI) adjustment and equals 1.38 in March 2024.

$$c_k^{\mathrm{acquisition}} = \frac{1}{n_{k,5yr}} \left(f^{\mathrm{CPI}}\, c_k^{\mathrm{airframe}} \right) + c_k^{\mathrm{propulsion}} + c_k^{\mathrm{avionic}} \tag{1}$$

The index k of all parameters and cost shares represents the dependence of different eVTOL vehicle configurations within the production cost model.

3.2.1. Airframe costs

Airframe costs comprise engineering, tooling, manufacturing, development support, flight test, quality control and material costs (see Eq. (2)). Within these costs, the influence of composite materials is considered, whereas additional certification costs are neglected as current eVTOL vehicles are to be certified according to CS-23 with special condition (Babetto et al., 2023; Gudmundsson, 2014).

$$c_k^{\mathrm{airframe}} = c_k^{\mathrm{engineering}}\, c_k^{\mathrm{tooling}}\, c_k^{\mathrm{manufacturing}}\, c_k^{\mathrm{devel}}\, c_k^{\mathrm{test}}\, c_k^{\mathrm{quality}}\, c_k^{\mathrm{material}} \tag{2}$$

The following detailed costs are based on parameterization approaches by Finger et al. (2019) and Gudmundsson (2014). While the latter focus on electric and hybrid-electric fixed-wing general aviation aircraft, their electric propulsion cost factors provide the best available foundation for eVTOL vehicle applications until detailed production data becomes available. Also, current production volume estimates are in line with the assumptions of series production (Inc., 2024).

Engineering costs are displayed in Eq. (3) with $m_{AS,k}$ being the structural airframe empty mass of vehicle k in lbs, $v_{max,k}$ being the maximum cruise speed in ktas, and f_k^{comp} being the factor of composite materials. If $f_k^{\mathrm{comp}} = 1$ then the airframe is fully built of composite materials. Q is the quantity of produced units within five years and R^{eng} are engineering labor costs. To account for additional engineering for eVTOL vehicles, Finger et al. (2019) consider an increase of 33 to 66 percent. Since Tilt-X concepts have more moving parts and are more complex than Multicopter and Lift + Cruise concepts, $f_k^{\mathrm{eng}} = 1.66$ is assumed for the first and $f_k^{\mathrm{eng}} = 1.33$ for the last two configurations.

$$\begin{aligned} c_k^{\mathrm{engineering}} &= \left[0.083\; m_{AS,k}^{0.791}\; v_{max,k}^{1.521}\; Q^{0.183}\; F_k^{\mathrm{comp}}\; R^{\mathrm{eng}} \right] f_k^{\mathrm{eng}} \\ &= \left[0.083\; m_{AS,k}^{0.791}\; v_{max,k}^{1.521}\; Q^{0.183}\; \left(1 + f_k^{\mathrm{comp}}\right)\; R^{\mathrm{eng}} \right] f_k^{\mathrm{eng}} \end{aligned} \tag{3}$$

Tooling costs are estimated based on Eq. (4) including additional 10 percent for Multicopter and Lift + Cruise concepts and additional 20 percent for Tilt-X concepts. This builds on Finger et al. (2019) and is further reasoned by high-voltage electric powertrains, where there may be potential increased costs for Tilt-X concepts due to the complexity of tilting mechanisms.

$$c_k^{\mathrm{tooling}} = \left[2.1036\; m_{AS,k}^{0.764}\; v_{max,k}^{0.899}\; Q^{0.178}\, Q_{mon}^{0.066}\; \left(1 + f_k^{\mathrm{comp}}\right)\; R^{\mathrm{tool}} \right] f_k^{\mathrm{tool}} \tag{4}$$

Manufacturing costs are shown in Eq. (5). In contrast to regional small aircraft considered by Finger et al. (2019) and Gudmundsson (2014), eVTOL configurations have fewer moving parts and simplified control surfaces, as flight control, take-off, and landing rely primarily on thrust adjustments rather than complex aerodynamic control systems and high-lift devices. Hence, a 20 percent reduction is calculated for Multicopter and Lift + Cruise configurations, while only a reduction of 10 percent ($f_{Tilt-X}^{\mathrm{man}} = 0.9$) is calculated for Tilt-X concepts where the mechanical simplification is less pronounced due to tilting mechanisms.

$$c_k^{\mathrm{man}} = \left[20.2588\; m_{AS,k}^{0.74}\; v_{max,k}^{0.543}\; Q^{0.524}\; \left(1 + 0.25\, f_k^{\mathrm{comp}}\right) R^{\mathrm{man}} \right] f_k^{\mathrm{man}} \tag{5}$$

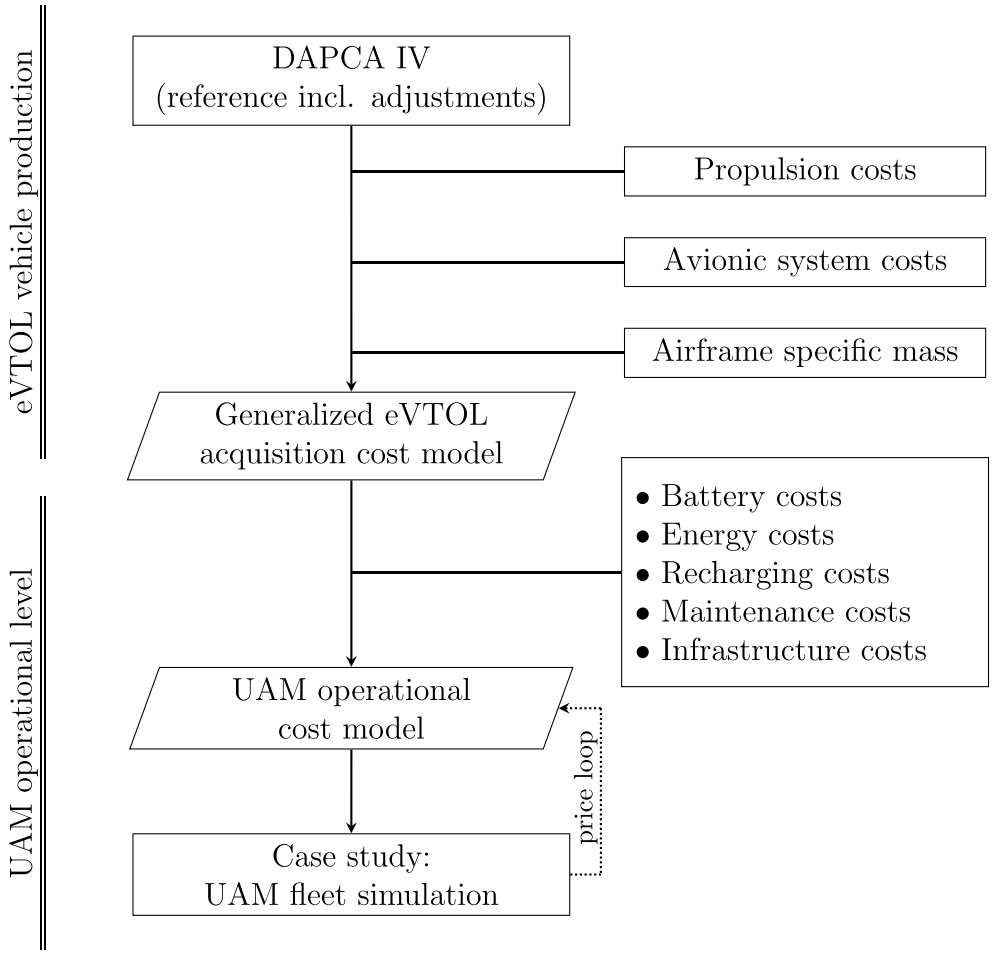


Fig. 1. Methodological approach for eVTOL vehicle cost modeling and operational cost analysis.

Development support costs have not yet been specified for eVTOL vehicle production. Therefore, a conservative assumption is used, setting ($f_k^{\text{devel}} = 1.5$) for all eVTOL configurations, as additional costs could occur within uncertain supply chains. This can be further reasoned as development support costs only account for a small proportion within the airframe costs. Q_{proto} is the number of prototypes used within the project and set to five by default (see Eq. (6)).

$$c_k^{\text{devel}} = \left[0.06458 \; m_{AS,k}^{0.873} \; v_{max,k}^{1.89} \; Q_{proto}^{0.346} \; \left(1 + 0.5 \; f_k^{\text{comp}}\right)\right] \; f_k^{\text{devel}} \tag{6}$$

Flight test operation costs for eVTOL vehicles are more complex and, in the context of ultralight aircraft, around ten times higher than for conventional small aircraft (Gudmundsson, 2014). Consequently, $f_k^{\text{test}} = 10$ is set as a conservative approach for all eVTOL configurations, although certification is to be carried out with special condition (see Eq. (7)).

$$c_k^{\text{test}} = \left[0.009646 \; m_{AS,k}^{1.16} \; v_{max,k}^{1.3718} \; Q^{1.281}\right] \; f_k^{\text{test}} \tag{7}$$

Quality control costs are to be estimated lower as less moving parts are to be inspected and checked. This applies for Multicopter and Lift + Cruise concepts, assuming a reduction of 20 percent ($f_k^{\text{quality}} = 0.8$) in Eq. (8). Tilt-X concepts are calculated by default without adjustments.

$$c_k^{\text{quality}} = \left[0.13 \; c_k^{\text{manufacturing}}\right] f_k^{\text{quality}} \tag{8}$$

Material costs are kept at the same level as for small aircraft in the base model (see Eq. (9)).

$$c_k^{\text{material}} = \left[24.896 \; m_{AS,k}^{0.689} \; v_{max,k}^{0.624} \; Q^{0.792}\right] \; f_k^{\text{material}} \tag{9}$$

3.2.2. Propulsion costs

Propulsion costs are divided into engine, electronics, and rotor costs and can be specified from both aviation-specific data and automotive industry data. Correction factors must be determined accordingly, including the QDF in line with the overall modeling (see Eq. (10)). A conservative correction factor for different eVTOL concepts (f_k^{corr}) is included with 1.1 for Multicopter and Lift + Cruise configurations and 1.3 for Tilt-X configurations. This is reasoned as Lift + Cruise concepts are often designed with both rotors and a pusher propeller. Tilt-X concepts are designed with additional electric servomotors and cause additional costs.

$$c_k^{\text{propulsion}} = \left(c_k^{\text{electronics}} + c_k^{\text{engine}} + c_k^{\text{rotor}}\right) \; f^{\text{QDF}} \; f_k^{\text{cons}} \tag{10}$$

The maximum required propulsion power defines the propulsion costs. The vertical climb performance is decisive and depends on the maximum vertical speed v^{vert}, the design gross mass (DGM) in kg, the disk area (A^{disk}) and efficiency factors η and f^{vert} (Kirste et al., 2023). DGM is the sum of empty mass and payload, where the structural airframe mass is a fraction of the empty mass. The required power for vertical climb is specific for different vehicle concepts k (see Eq. (11)).

$$P^{\text{vert}} = \frac{1}{\eta^{\text{vert}}} \left(f_k^{\text{vert}} \; m_k^{\text{DGM}} \; g \sqrt{\frac{m_k^{\text{DGM}} \; g}{2 \; \rho^{\text{air}} \; A_k^{\text{disk}}}} + \frac{m_k^{\text{DGM}} \; g \; v^{\text{vert}}}{2} \right) \tag{11}$$

Engine costs result from the maximum shaft power and the cost factor ζ_k^{engine}, which is set at $ 172/kW as an average from recent publications (Finger et al., 2019; Hoelzen et al., 2018). Also, a power reserve factor (f_k^{reserve}) of 1.2 is considered. For eVTOL vehicles, a safety factor is required that enables continued flight and at least a

controlled descent in the event of rotor failure as well as in difficult flight conditions. Accordingly, this is addressed with a power reserve factor (f_k^{hover}) for the vertical rotor units, which is in line with currently published data and set to 50 percent for Multicopter and 30 percent for Lift + Cruise and Tilt–X configurations. Due to the higher lift-to-drag ratio of concepts with fixed wings, a lower safety factor is reasoned. As the first requirement depends on the vertical climb rate, the maximum of both requirements is set for the engine sizing and cost estimation in Eq. (12). No distinction is made between different numbers of rotors.

$$c_k^{\text{engine}} = \zeta^{\text{engine}} \; max \; \left(P_k^{\text{vert}} \; f_k^{\text{reserve}} \; , \; P_k^{\text{hover}} \; f_k^{\text{hover}} \right) \tag{12}$$

Electronic costs are determined by the product of the maximum required power by a cost factor $\zeta^{\text{electronics}}$ set to $ 86/kW referring to Finger et al. (2019).

$$c_k^{\text{electronics}} = \zeta^{\text{electronics}} \; P_k^{\max} \tag{13}$$

Rotor costs are modeled based on the approach by Gudmundsson (2014). Hence, the rotor specific cost factor (ζ^{rotor}) is set to $ 3145 per rotor and multiplied by the number of rotors of eVTOL vehicle concept k. Update has been carried out by the CPI. The specific rotor size is not included in the cost estimation model, but considered due to the adjustments in rotor power costs (see Eq. (14)).

$$c_k^{\text{rotors}} = \left(\zeta^{\text{rotor}} \; n_k^{\text{rotor}} \right) \; CPI \tag{14}$$

3.2.3. Avionic costs

Avionic costs result from the basic costs (ζ^{base}) and additional costs for autonomous flight operations (ζ^{auto}). Since cost estimations by Gudmundsson (2014) refer to small aircraft without autonomy, recent studies need to be taken into account. These are carried out by various researchers: Holden and Goel (2016) estimate the base cost at $ 100,000 plus additional $ 60,000 for autonomy, while Cohen et al. (2021) estimate $ 50,000 plus $ 60,000. Brown and Harris (2020) estimate the total costs at $ 100,000. Only Holden and Goel (2016) include a QDF based on 500 vehicles per year. Hence, both base costs and additional autonomy costs are set to an average of $ 60,000 considering additional QDF (see Eq. (15)). This assumption is in line with the forecast by Cohen et al. (2021) that prices will likely halve by 2030. As Holden and Goel (2016) also include the passenger capacity (n_k^{PAX}) in their assumption, variations in passenger capacity are included with $ 5,000 for digital screens and systems per passenger.

$$\begin{aligned} c_k^{\text{avionics}} &= \left[\zeta^{\text{base}} + f_k^{\text{autonomy}} \; \zeta^{\text{auto}} + \zeta_k^{\text{PAX}} \right] \; QDF \\ &= \left[\zeta^{\text{base}} + f_k^{\text{autonomy}} \; \zeta^{\text{auto}} + \zeta^{\text{4PAX}} \; \left(n_k^{\text{PAX}} - 4 \right) \right] \; QDF \end{aligned} \tag{15}$$

3.2.4. Quantity discount factor modeling

The QDF is relevant to adjust the cost model to the research gap on the one hand and the modeling approach of structural airframe costs and propulsion costs on the other. Based on Gudmundsson (2014), the factorial cost reduction for a production volume can be calculated. According to the author, the experience effectiveness due to increased performance and skill optimization is estimated at 0.95 in aviation (see Fig. 2). Holden and Goel (2016) estimate this value to 0.85 which leads to a cost reduction of over 80 percent for a production volume of 1,000 units or more (see dotted graph in Fig. 2). For further calculations and analyses, 0.95 experience effectiveness is used as default considering series production in aviation.

3.2.5. Operational costs

Operational costs on fleet level are considered based on a Total Cost of Ownership (TCO) approach extending recent research. TCO for UAM operation are shown in Eq. (16) and include costs for building the vertiport infrastructure (C_{vi}), charging infrastructure (C_{ci}), air traffic management (C_{atm}), vertiport operational processes (C_{vop}), acquisition of the vehicle fleet (C_{ac}), batteries (C_{br}), maintenance of the vehicle

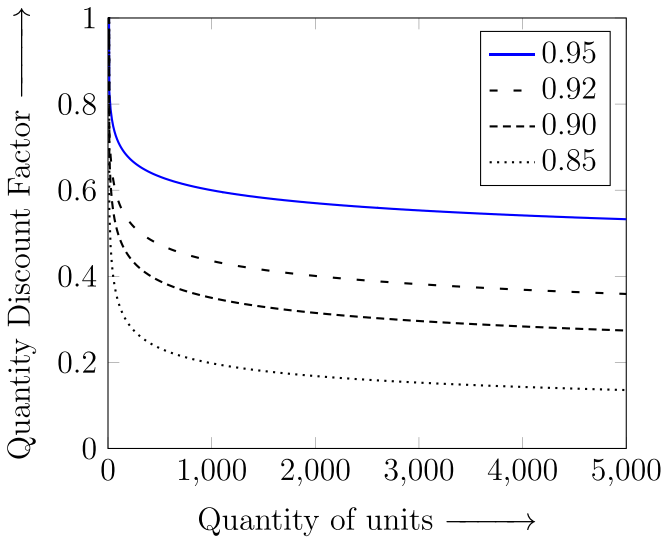


Fig. 2. Modeled QDF based on Equation (2–1) by Gudmundsson (2014).

fleet (C_{mx}), energy (C_{en}), and flight crew (C_{fc}). Insurance costs are initially neglected, but can be qualitatively considered in the overall study evaluation by analyzing sensitivities and profit margin. Similarly, system-wide unmanned traffic management (UTM) infrastructure costs for lower airspace automation are not explicitly modeled due to ongoing regulatory development and technical testing, requiring analogous qualitative assessment.

$$TCO = C_{vi} + C_{ci} + C_{atm} + C_{vop} + C_{ac} + C_{br} + C_{mx} + C_{en} + C_{fc} \tag{16}$$

Infrastructure costs for the construction of the vertiports within the UAM network are calculated by the number of vertiports (n_{vp}) and costs for building each vertiport (c_{netw}) in Eq. (17). For converting total lifetime costs into TCO per operating day, the economic lifetime in years (a_{UAM}) and the number of annual operating days (σ) are considered.

$$C_{vi} = \frac{c_{netw} \; n_{vp}}{a_{UAM} \; \sigma} \tag{17}$$

Costs for the charging infrastructure are based on hardware costs (c_{hw}) and installation costs (c_{ins}) for each high power charger (see Eq. (18)). It is conservatively assumed that one charger is applied for each parking slot at the vertiports (n_{ps}).

$$C_{ci} = \frac{n_{vp} \; n_{ps} \; (c_{hw} + c_{ins})}{a_{UAM} \; \sigma} \tag{18}$$

For air traffic management costs, monitoring personnel is considered for each vertiport (see Eq. (19)). Hence, these total costs are modeled by including the number of labor shifts (n_{shifts}) and the annual salary per person (c_{salary}).

$$C_{atm} = \frac{n_{vp} \; n_{shifts} \; c_{salary}}{\sigma} \tag{19}$$

Operational costs for each vertiport are displayed in Eq. (20). To account for varying fleet sizes (n_{fleet}), C_{vop} is based on annual operating costs per vehicle (c_{netop}). The minimum required fleet size is modeled as function of boarding, takeoff, cruise flight, landing, de-boarding, turnaround, and buffer time (Kirste & Stumpf, 2025).

$$C_{vop} = \frac{c_{netop} \; n_{fleet}}{\sigma} \tag{20}$$

Fleet acquisition costs are included based on the detailed production cost model in Section 3.2 and incorporate eVTOL specific economic lifetime (a_{eVTOL}), residual value (ξ), acquisition costs (c_{acq}) with a profit margin for the manufacturer (f_{margin}), and the foreign exchange

rate (fx_{UE}) converting production costs of US-Dollar into Euros (see Eq. (21)).

$$C_{ac} = f_{margin}\ \frac{n_{fleet}\ c_{acq}\ (1-\xi)}{a_{eVTOL}\ \sigma}\ \frac{1}{fx_{UE}} \tag{21}$$

Battery costs including battery replacement over the lifetime are modeled based on the battery specific cost factor (c_{bat}), the number of recharging cycles (n_{bat}), and the total energy consumption (E_{total}) of the eVTOL fleet (see Eq. (22)). It should be noted that C_{br} are modeled as operational costs since recharging cycle costs depend on the energy consumption and battery mass is set in line with the required flight range.

$$C_{br} = \frac{c_{bat}\ E_{total}}{n_{bat}} \tag{22}$$

Maintenance costs are calculated as function of maintenance cost factor (c_{maint}) and the total flight time (see Eq. (23)) (Holden & Goel, 2016; Kirste & Stumpf, 2025). The total flight time accounts for all takeoff ($t_{t/o}$), landing (t_{ldg}), and vertical flight phases (t_{vert}) as well as the total cruise time based on the cruise speed (v_{cruise}). *count* and *distance* describe the number of UAM passenger trips and the total UAM travel distance for all passengers of the UAM demand model.

$$C_{mx} = c_{maint}\left[count\ (t_{t/o} + t_{vert} + t_{ldg}) + \frac{distance}{v_{cruise}}\right] \tag{23}$$

Energy costs are displayed in Eq. (24) and are based on energy price (c_e), total energy consumption in all flight segments, additional detour factor for deadheading flights (f_{dh}), and maneuvering factor (η_{man}).

$$\begin{aligned} C_{en} &= c_e\ E_{total} \\ &= c_e\ E_{mission}\ f_{dh}\ \eta_{man} \end{aligned} \tag{24}$$

For hovering and vertical flight segments, the disk actuator theory is applied (see Eq. (25)). Extensions are set due to the average load factor of flight specific passenger pooling (LF_{avg}), the total number of UAM trips, and the efficiency factor of the vertical flight system of each eVTOL configuration (f_{vert}).

$$e_{vert} = \frac{count\ t_{vert}\ f_{vert}}{LF_{avg}}\left(MTOM\ g\sqrt{\frac{MTOM\ g}{2\ \rho_{air}\ A_{disk}}} + \frac{MTOM\ g\ v_{vert}}{2}\right) \tag{25}$$

Energy consumption in cruise phases is modeled in Eq. (26), where Eq. (27) specifies the lift coefficient and Eq. (28) specifies the drag coefficient. κ includes both Oswald factor and Aspect Ratio. It is noted that $\eta_{L/D}$ is an additional factor to account for reduced lift-to-drag ratio in climb and descend flight segments.

$$e_{cruise} = \frac{1}{LF_{avg}\ \eta_{L/D}}\ \frac{MTOM\ g}{\eta_{cruise}\ c_L/c_D}\ distance \tag{26}$$

$$c_L = \frac{2\ MTOM\ g}{\rho_{air}\ {v_{cruise}}^2\ S_{wing}} \tag{27}$$

$$c_D = c_{D0} + \kappa\ {c_L}^2 \tag{28}$$

In total, a seven segment flight profile approach is modeled. A representative flight with an altitude of 150 m and 40 min cruise is displayed in Fig. 3. The corresponding flight mission specifications are summarized in Table 2. Additionally, turnaround, boarding, and deboarding are considered for overall eVTOL utilization and UAM travel times. The vertiport operating factor accounts for vertiport processes and flexibility within take-off and landing procedures.

Costs for the flight crew are modeled based on the annual salary of eVTOL pilots (c_{pilot}), the number of flight crews to enable daily operations (n_{crew}), and the eVTOL fleet size (see Eq. (29)). f_{pilot} is set as binary variable and equals one if piloted operations are considered instead of autonomous flight operations.

$$C_{fc} = \frac{f_{pilot}\ c_{pilot}\ n_{crew}\ n_{fleet}}{\sigma} \tag{29}$$

Table 2
Mission specific parameters.

Parameter	Explanation	Value	Unit
t_{seg1}	Hovering	30	s
t_{seg2}	Vertical climb	30	s
t_{seg3}	Climb	30	s
t_{seg4}	Cruise	$=\frac{distance}{v_{cruise}}$	s
t_{seg5}	Descend	30	s
t_{seg6}	Vertical descend	30	s
t_{seg7}	Hovering	30	s
$t_{alternate}$	Alternate	15	min
t_{tat}	Tournaround	360	s
t_{board}	Boarding	60	s
$t_{deboard}$	Deboarding	60	s
t_{vop}	Operating factor	2	–

Table 3
Structural airframe mass of eVTOL configurations.

eVTOL concept	$\frac{m_{AS}}{m_{DGM}}$	$\frac{m_{AS}}{m_{empty}}$	$\frac{m_{AS}}{m_{empty}^{w/o.Bat}}$	Sources
Multicopter	0.27	0.34	**0.51**	mean
	n/a	n/a	n/a	(Duffy et al., 2017)
	0.25	0.31	0.44	(Silva et al., 2018)
	0.28	0.35	0.52	(Johnson et al., 2018)
	0.27	0.35	0.56	(André, 2022)
Lift + Cruise	0.30	0.37	**0.54**	mean
	0.27	0.35	0.50	(Duffy et al., 2017)
	0.31	0.37	0.49	(Silva et al., 2018)
	n/a	n/a	n/a	(Johnson et al., 2018)
	0.31	0.39	0.63	(André, 2022)
Tilt-X	0.27	0.37	**0.53**	mean
	0.26	0.33	0.45	(Duffy et al., 2017)
	n/a	n/a	n/a	(Silva et al., 2018)
	0.25	0.39	0.56	(Johnson et al., 2018)
	0.31	0.38	0.59	(André, 2022)

Note: Values are computed and partially deducted from figures.

4. Study design

To analyze the total costs of UAM operations, studies are carried out at both vehicle and fleet level. Here, relevant eVTOL vehicle data, cost parameter settings, and demand simulation are required.

4.1. eVTOL data

First, the configuration-specific parameters are considered. In addition to the model extension (see Section 3.2), these are the fractions of masses as input data for all structural airframe cost functions. In recent literature, the design gross mass, empty mass, and battery mass have been analyzed for eVTOL performance calculation and optimization. A detailed calculation of the structural airframe mass is carried out by André (2022), Duffy et al. (2017), Johnson et al. (2018), and Silva et al. (2018). Here, more complex Lift + Cruise and Tilt-X configurations have a higher structural airframe mass. However, the fraction of structural airframe mass to DGM and empty mass deviates (see Table 3). Hence, a generalized approach to airframe mass is applied considering the mass fraction in relation to the empty mass without battery. This avoids biases in absolute values. The bold values in Table 3 represent the mean averages used as default values in the modeling.

Second, vehicle performance parameters are included. Since a comprehensive cost analysis for eVTOL vehicles requires detailed vehicle data, the following 11 vehicle concepts are considered by incorporating recent studies: (Babetto et al., 2023; Chauhan & Martins, 2020; Fredericks et al., 2018; Kirste & Stumpf, 2025; Lee et al., 2020)

k = 1 Lift + Cruise configuration based on the *Aurora PAV* concept,
k = 2 Tilt-Wing configuration based on the *A3 Vahana* concept,
k = 3 Lift + Cruise configuration based on the *EHang VT-30* concept,

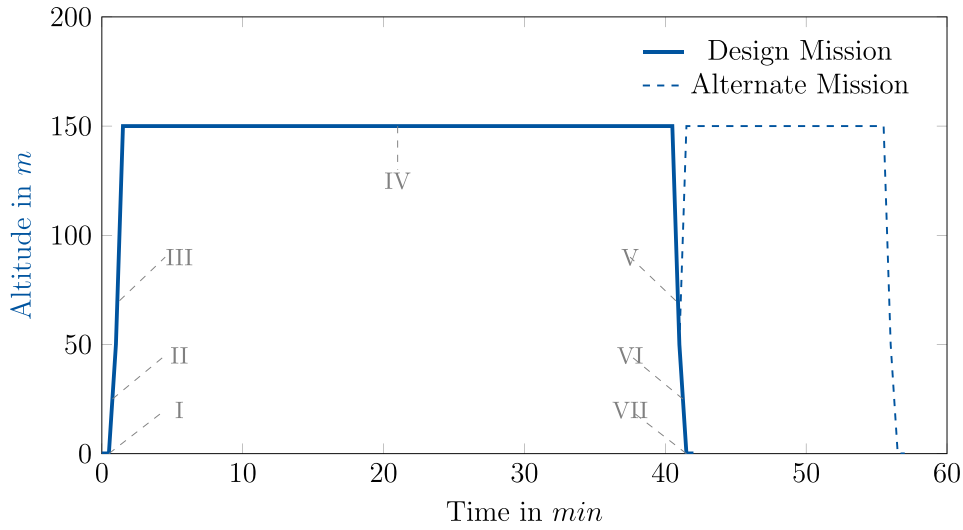


Fig. 3. UAM flight mission profile for an exemplary 40 min cruise flight.

Table 4
Studied eVTOL vehicles for autonomous flight operations.

k	Vehicle	PAX[a]	MTOM	v_{max}
k = 1	Aurora PAV	2	800 kg	50 m/s
k = 2	A3 Vahana	1	815 kg	50 m/s
k = 3	EHang VT-30	2	880 kg	36 m/s
k = 4	Wisk Gen. 5	2	1404 kg	50 m/s
k = 5	City Airbus NextGen	4	2360 kg	33 m/s
k = 6	Joby S4	5	2400 kg	89 m/s
k = 7	Wisk Gen. 6	5	2500 kg	61 m/s
k = 8	Archer Midnight	5	3175 kg	67 m/s
k = 9	Beta Alia 250	6	3175 kg	69 m/s
k = 10	EHang 216	2	580 kg	36 m/s
k = 11	VoloCity	2	900 kg	30 m/s

[a] The total PAX number is considered for autonomous flight operations.

Table 5
MATSim UAM simulation parameters.

Simulation parameter	Value	Unit
Population data	1	%
Number of vertiports	55	–
Charging slots per station	4	–
Innovative iterations per simulation	135	–
Total iterations per simulation	150	–
Process times	5 – 20	min
Cruise speed	25 – 90	m/s
Range	20 – 99	km
UAM fixed base price	0 – 20	€
UAM variable price	0.80 – 2.00	€/pkm

k = 4 Lift + Cruise configuration based on the *Wisk Cora Gen. 5* concept,
k = 5 Lift + Cruise configuration based on the *City Airbus NextGen* concept,
k = 6 Tilt-Rotor configuration based on the *Joby S4* concept and assuming that the initial pilot on board could be substituted by an additional passenger in the near future,
k = 7 Tilt-Rotor configuration based on the *Wisk Gen. 6* concept,
k = 8 Tilt-Rotor configuration based on the *Archer Midnight* concept,
k = 9 Lift + Cruise configuration based on the *Beta Alia 250* concept,
k = 10 Multicopter configuration based on the *EHang 216* concept with co-axial rotor design,
k = 11 Multicopter configuration based on the *VoloCity* concept.

These eVTOL vehicle data are summarized in Table 4. It is noted that cruise flight performance data of Multicopter configurations are currently relatively uncertain. Therefore, an average lift-to-drag ratio of 1.5 to 2.5 is set. Also, battery masses are modeled to meet the maximum profit design range. Hence, the displayed Maximum Take-Off Mass (MTOM) values could be reduced in the analysis and evaluation stage, depending on the optimal design range.

Third, production model parameters are set according to Section 3.2 including CPI of 1.38 and QDF of 0.95. A vehicle production rate of 500 units per year is considered as the base case for 2030 (Holden & Goel, 2016). This is conservatively adjusted based on a production volume of 650 eVTOL vehicles, as published by Inc. (2024), for a near-term scenario that begins in five years. The exchange rate used to calculate in a reference currency is one euro to US-$ 1.08. Furthermore, an average mass increase of 30 percent for aluminum and non-composite materials is included in the power and energy calculation.

4.2. Operational scenario

The initial operational scenario is the *Metropolitan Region Rhine–Ruhr* in Germany. Ziemke et al. (2019) With a maximum horizontal distance of 100 km, this represents a transition zone towards regional air mobility. The simulation basis of the UAM operation is the Multi-Agent Transport Simulation (MATSim) developed by Horni et al. (2016), extended by Balac et al. (2019) and Rothfeld et al. (2018), and applied and analyzed in the Rhine–Ruhr area. Input and configuration data are drawn from open access repositories (e.V., 2024; Transport Systems Planning and Transport Telematics & Technische Universität Berlin, 2024). It is to be noted that mode choice behavior of the agents is in line with ground-based transportation, focusing on travel time savings and mode ticket prices. Additional adjustments for UAM preferences (positive or negative), e.g. based on comfort of eVTOL flights, are neglected at this point. Similar to uncertain cost parameters, an evaluation of further utility or disutility could be interpreted qualitatively based on input parameter sensitivities. Since the agents choose their preferred mode based on the trip costs and time savings, UAM can be simulated as a mobility service in competition with other transportation modes. 55 vertiports are implemented and capacity limitations of four vehicles for recharging at the same time at the vertiports are modeled. The operational and simulation parameters are summarized in Table 5.

Utilizing a data set of 100 simulation instances within these simulation parameter ranges, a surrogate demand model can be drawn (Kirste & Stumpf, 2025). The number of UAM trips ($count$) is modeled as regression function of fixed ticket price ($fixprice$), variable ticket price per

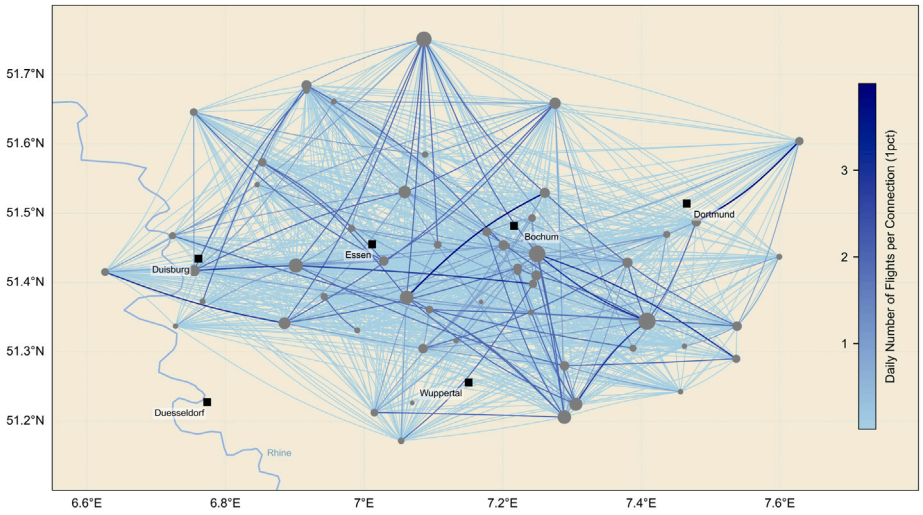


Fig. 4. Exemplary study instance of simulated UAM flights that maximize the overall utility of the agents (150th iteration).

passenger kilometer (*varprice*), eVTOL vehicle range (*range*), eVTOL cruise speed (v_{cruise}), and process times for UAM trips (*process*). For the number of trips and the total distance of all eVTOL vehicles, Eq. (30) and Eq. (31) apply. This allows computing the operator's revenue for variable eVTOL configurations. Here, the positive coefficients for ticket price parameters may appear counterintuitive but reflect that prices enter as negative values in the configuration setup. Therefore, less demand results for increasing ticket prices (Kirste & Stumpf, 2025). It is noted that process times of 15 min are set as default and conservative scaling up to 90% demand is applied for further analyses.

$$count \approx 175.71 + 5.53\ fixprice + 56.71\ varprice + 0.13\ range + 0.26\ speed - 0.90\ process \quad (30)$$

$$distance \approx 1803.21 + 50.46\ fixprice + 661.01\ varprice + 2.39\ range + 2.26\ speed - 8.25\ process \quad (31)$$

Fig. 4 shows an exemplary simulation study instance with average ticket prices in the 1% scenario. It is noted that the resulting set of flight sequences only include UAM trips that increase the overall utility of the agents as the innovation strategy of MATSim is switched off after 135 iterations.

4.3. Parameter settings

Further, cost and operational parameters are to be set for the TCO model. Table 6 summarizes infrastructure costs to derive C_{vi} and C_{vop}. Literature estimates for small and medium-sized vertiport construction costs vary significantly (0.2 to over 3.5 million euros per station) depending on capacity and design specifications (Butterworth-Hayes, 2024; Holden & Goel, 2016; McKinsey & Company, 2020; Santha et al., 2023; Schweiger & Preis, 2022). It is noted that vertiport investment and construction costs of other research are based on different vertiport layouts. Due to the limitation of four charging slots per station, only vertiport designs with a similar capacity are included. For construction costs, one million euros per station are set as default considering an economic lifetime of conservative 13 years. Operational costs are modeled as additional annual costs per eVTOL vehicle so that different fleet sizes are represented (Holden & Goel, 2016). After the economic lifetime period, which is also estimated for the vehicles, further conversion measures may be necessary at the vertiports. It is noted that some values are converted from US-Dollar to Euros.

Table 7 shows all other TCO model parameter value ranges and default settings. Technological developments up to 2030 are considered. Specifically, a battery specific energy density of 400 Wh/kg, 1250 charging cycles with respect to peak power reductions, 80% battery reserve (μ), and 75% vehicle cruise efficiency are set. The average load factor is modeled as 1 for the first passenger and 0.5 for each additional passenger through pooling inefficiencies (see Eq. (32)). This results in $LF_{avg} = 3$ for an eVTOL with 5 PAX. Additional 20% empty flights are considered for re-routing. Further, 300 annual operating days are considered to account for availability reduction due to weather uncertainties.

Table 6
Infrastructure costs for vertiports.
Source: (A) Schweiger and Preis (2022), (B) Santha et al. (2023), (C) McKinsey & Company (2020), (D) Butterworth-Hayes (2024), (E) Holden and Goel (2016).

Reference	Construction in Mio.€/station	Operation in Mio.€/yr	Lifetime in years
A	0.35–0.75	n.a.	n.a.
B	≥ 3.5	n.a.	n.a.
C	0.2–0.8	0.6–5	n.a.
D	0.3–0.4	0.7–1.3	n.a.
E	1.28	0.075/eVTOL	n.a.
This paper	1	0.075/eVTOL	13

$$LF_{avg} = 1 + 0.5\ (PAX - 1) \quad (32)$$

20% deadheading and an average pooling factor of $1+0.5(PAX-1)$ with 15 min process times at vertiports,

5. Results

Study results are analyzed on eVTOL vehicle level, on fleet level, and regarding sensitivities.

5.1. Analysis of eVTOL vehicle costs

For the base case of a production volume of 500 eVTOL vehicles per year, the eVTOL vehicle production costs result in between $ 178,000 and $ 616,000 (see Table 8 and data points in Fig. 5 with deviations in the annual production volume between 100 and 1000). For the estimated production volume of an initial UAM phase (20 vehicles per year), production costs result in between $ 300,000 and $ 2,000,000. The initial cost differences are particularly in the following parameters: maximum cruise speed, Tilt-X concepts, and high structural mass. For high quantities, the correlation between costs and structural mass

Table 7
Parameters for 2030 base case analysis.

Parameter	Unit	Value range	Default
Battery technology			
n_{bat}	–	750–2000	1250
ρ_{energy}	kWh/kg	200–500	400
ρ_{power}	kW/kg	3–18	≥ 3
μ	–	0.6 - 0.95	0.8
Costs			
c_{bat}	€/kWh	200–350	250
c_e	€/kWh	0.25–0.35	0.30
c_{hw}	€/charger	25–122	122k
c_{ins}	€/charger	40–58	58k
c_{maint}	€/FH	20–110	50
c_{netop}	€/(eVTOL · a)	variable	75k
c_{netw}	Mio €	0.5–3.5	1.0
c_{pilot}	€/a	30k–100k	50k
c_{salary}	€/a	30k–70k	50k
Other			
a_{eVTOL}	yr	5–30	13
a_{UAM}	yr	10–50	13
f_{dh}	–	1.0–1.5	1.2
f_{margin}	–	variable	1.05
f_{pilot}	binary	0;1	0
fx_{UE}	USD/€	1.00 - 1.20	1.08
n_{crew}	–	n.a.	2
n_{shifts}	–	n.a.	2
n_{ps}	–	3–5	4
n_{vp}	–	scenario	55
η_{cruise}	–	0.7–0.8	0.75
$\eta_{L/D}$	–	0.8–0.9	0.86
η_{man}	–	1.0–1.2	1.1
ξ	–	0–0.5	0.3
σ	–	250–350	300

Table 8
Resulting production cost estimates.

eVTOL	Annual production volume				Add. battery
	20/yr	100/yr	500/yr	1000/yr	(400 Wh/kg)
k = 1	453	259	187	160	26
k = 2	649	344	223	195	25
k = 3	426	254	178	159	26.4
k = 4	818	450	299	262	40
k = 5	913	526	357	314	63
k = 6	1998	901	505	421	58.5
k = 7	1511	762	469	403	75
k = 8	2013	1005	616	528	95.3
k = 9	1700	837	509	435	95.3
k = 10	310	204	155	142	17.5
k = 11	379	238	173	156	32

All cost estimates are displayed in 1,000 USD. Battery costs are $ 250/kWh.

Table 9
Resulting cost factors for eVTOL vehicles.

Production volume	Surrogate model regression	R^2
Previous research	range from 500 to 1100 $/kg	n.a.
Initial phase (100 units/5yr)		
All configurations	$ 76756 + $ 1007/kg	0.85
Lift + Cruise	$ 94923 + $ 823/kg	0.86
Tilt-X	$ 293695 + $ 1005/kg	0.87
Future phase (2500 units/5yr)		
All configurations	$ 82084 + $ 272/kg	0.92
Lift + Cruise	$ 93079 + $ 228/kg	0.95
Tilt-X	$ 92429 + $ 297/kg	0.98

increases, and the value range specifies forecasts by Holden and Goel (2016), namely between $ 200,000 and $ 600,000.

Analyzing the detailed cost shares, airframe costs account for the largest share for all vehicles and production volumes. Considering the initial phase, airframe costs account for nearly half the costs for Multicopter (k = 10) and 80% the costs for Tilt-Rotor (k = 6). In case of k = 10, propulsion costs are relatively high as the power requirements for all flight phases are decisive (see Fig. 6). For the future phase in 2030, the total vehicle costs for k = 6 (Tilt-Rotor) amount to $ 563,500 when battery costs are added at $ 250/kWh. These costs are comparable to initial UAM cost models by Holden and Goel (2016), with insurance included. Nevertheless, there are deviations in the development costs as part of the airframe costs, which account for a larger share than in previous research. Regarding Fig. 5, the costs for Multicopter concept k = 10 can be modeled at less than $ 300,000 for a production volume in 2030 that is below the current market price (EHang, 2024). Instead, the overall model result can be seen as validated for a production volume of 100 vehicles within 5 years as it provides the published data (see Table 8). The deviations based on the quantity of units are specific to both the mass and the propulsion of the eVTOL vehicles. The deviations for higher production quantities (lower costs) generally follow the implemented QDF and limit the uncertainty to lower costs.

Based on the shaded areas in Fig. 5, the results can be compared with recent publications on mass-specific cost modeling by Brown and Harris (2018, 2020) and Kohlman et al. (2019): The recent cost estimates only represent an average for lower production quantities (high costs). Accordingly, a general adoption of the cost model presented here could enhance the overall UAM service analyses as the technology maturity level of UAM further increases. Analyzing the cost breakdown further, there is a relevant deviation for heavier eVTOL vehicles in comparison with recent literature, while small vehicles tend to be relatively more expensive depending on the production volume. This is expected because avionic and propulsion costs are non-linear and do not increase in direct proportion to the empty mass for larger eVTOL concepts.

Table 9 shows the linear surrogate regression models for both initial and future production volumes. The gradients of the surrogate equations vary between the considered configurations. Configuration-specific models are more accurate in terms of the coefficient of determination. Here, a positive intercept can be assessed as model-improving in comparison to previous linearizations, as this reflects the basic costs that are inherent to any production process. It can be derived that these surrogate models can already increase the accuracy of existing cost estimates without directly implementing parametric cost estimates.

While predefined airframe cost parameters were partially set, propulsion and avionic costs also depend on the modeled QDF. Fig. 7 shows the sensitivity of production volume and QDF for the two exemplary vehicles k = 6 and k = 10. It can be stated that lighter vehicles are sensitive to the QDF modeling assumption, as propulsion and avionic costs account for a large proportion of the total production costs. For heavier eVTOL vehicles, this effect is small in relative terms, as airframe costs still account for the largest share in all parameter sensitivities.

In addition to the production quantity, sensitivity analysis is also relevant for the modeling of materials, in particular composite materials (see Section 3.2). Fig. 8 depicts an example of the study of concepts k = 6 and k = 10. The total acquisition costs as a function of the composite fraction and the production volume indicate that the use of aluminum could be reasoned on the basis of production costs alone. For example, the costs of the Tilt-Rotor concept are up to 17 percent lower for a production volume of 100 vehicles per year when used without composite materials. Nevertheless, this effect is offset when considering reference flight missions. Additional structural mass increases energy consumption, particularly in the hovering and vertical climb segments. This leads to an increase in the required battery mass and further increased energy consumption. Partial hybrid modeling cannot provide a cost advantage over the fully composite structure in all studies. This snowball effect is evident in all parameter settings considered, meaning that eVTOL designs using aluminum can be considered cost-inefficient.

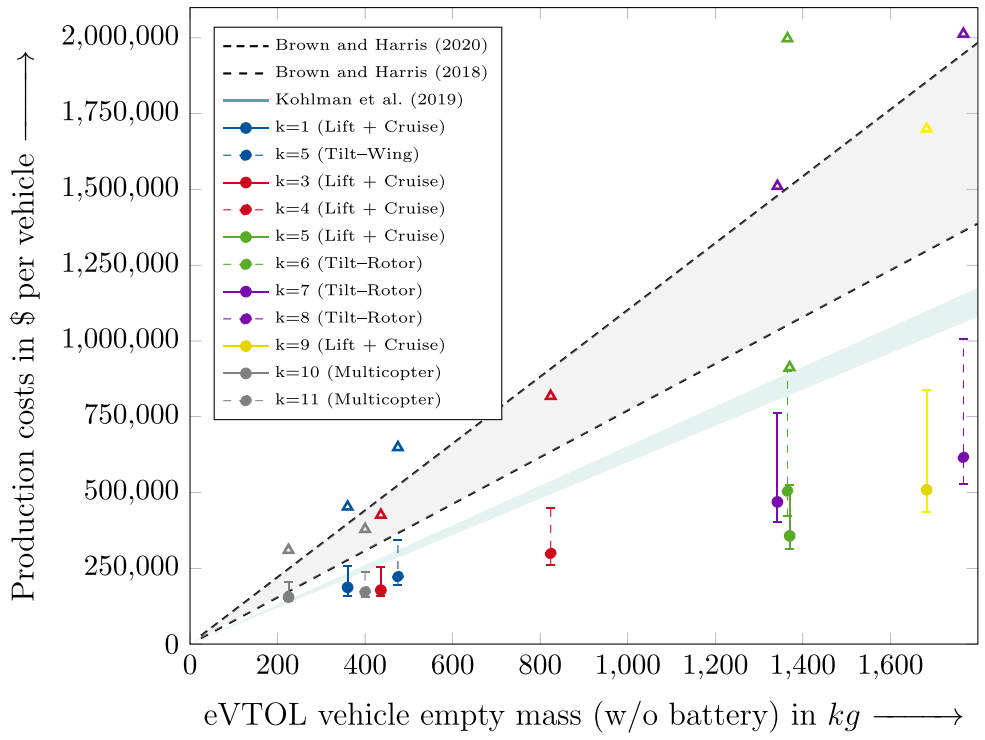


Fig. 5. Computed production costs with variable quantity. Triangular markers represent an annual production volume of 20 vehicles, dashed lines represent 100 to 1000 vehicles, and highlighted dots represent the 2030 base case of 500 vehicles. MTOM dependencies from other literature are color-coded in the background.

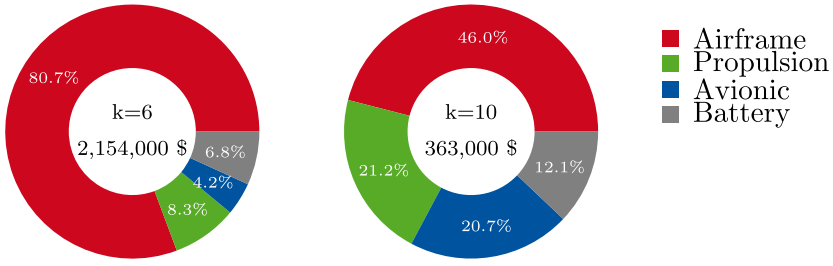


Fig. 6. Cost breakdown comparison of Multicopter and Tilt-Rotor vehicle configurations.

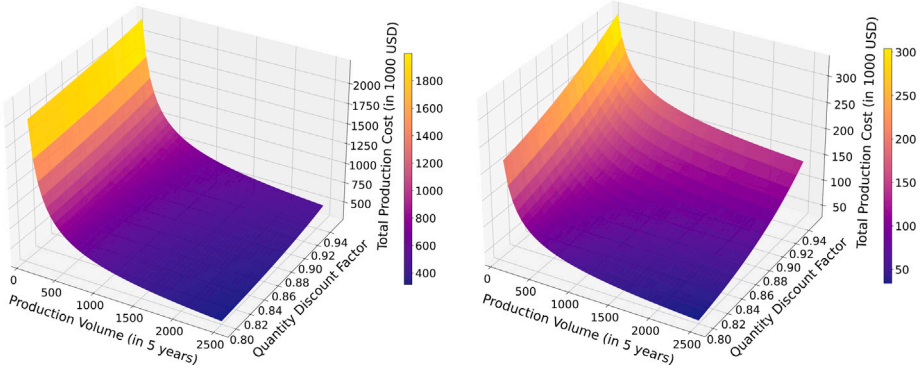
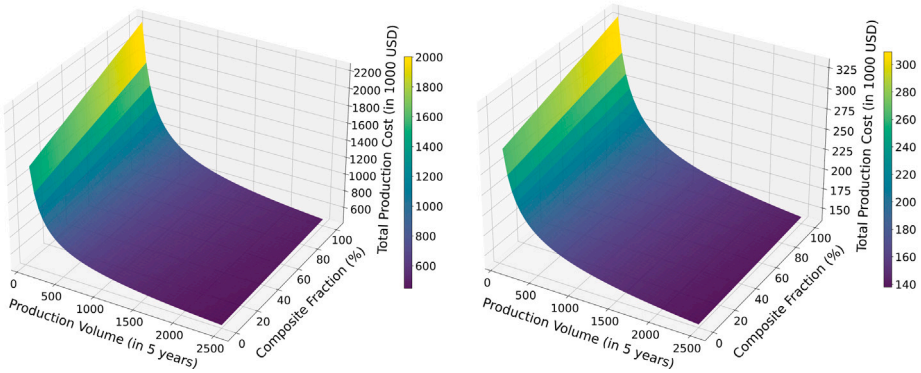


Fig. 7. Production costs for variable QDF and production volume.

It is noted that for some eVTOL concepts, there is already a partial reversal effect of the production costs for fully composite vehicles. For example, the Lift + Cruise concept k = 1 indicates lower production costs for fully composite designs from a quantity of 5,000 vehicles per year (while comparing mass and required power interactions). In this case, the different power requirements of the respective design range affect the propulsion costs more than the airframe costs. This is due to the more pronounced exponential reduction through learning effects in airframe costs. It is noted that this effect only applies with very high quantities far above series production volumes.



(a) eVTOL vehicle $k = 6$ (b) eVTOL vehicle $k = 10$

Fig. 8. Production costs for variable composite fraction and production volume.

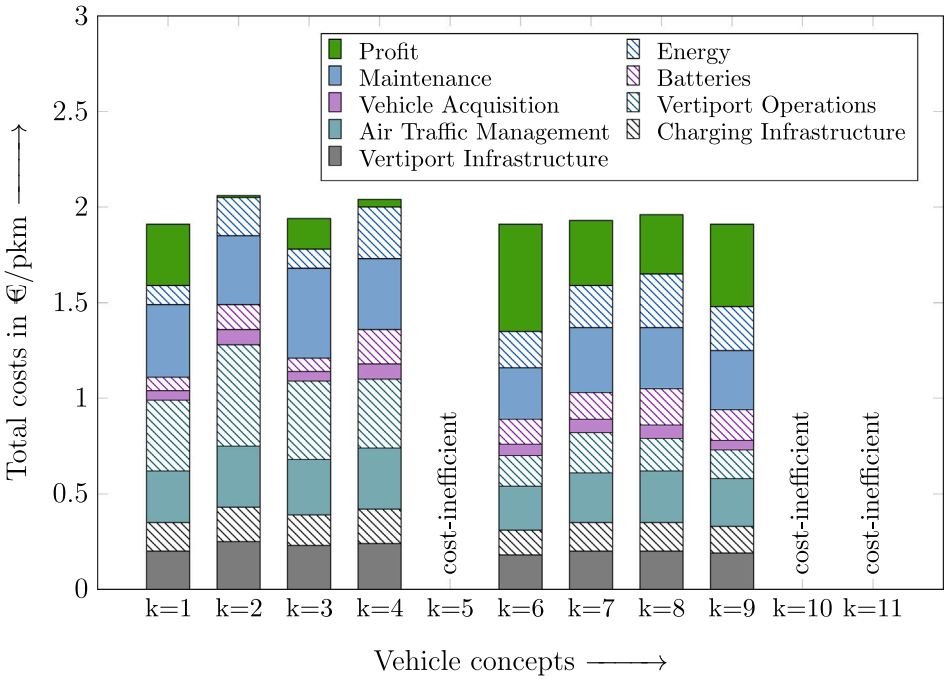


Fig. 9. Total costs for eVTOL vehicle concepts with base case values.

5.2. Total costs on fleet level

Based on demand simulation and total cost modeling, the profit optimum can be determined for each eVTOL vehicle. This is derived from the base case assumptions and takes into account profit-maximizing cruise speed and battery mass. Profit maximization is performed by using Gurobi Python. Fig. 9 shows the results for the various eVTOL vehicles. It can be stated that all vehicles are technically feasible considering autonomous flight operations and a battery specific energy density of 400+Wh/kg in the 2030 base case. Vehicles k = 5, k = 10, and k = 11 are cost-inefficient, as the maximum possible revenue cannot cover the resulting total costs, including infrastructure costs. For the other eVTOL vehicles, a potential business case arises with varying cost splits. It is shown that larger vehicle concepts in particular are profitable, as maintenance costs and vertiport operating costs are low. This is due to the smaller fleet size. Furthermore, average prices are comparable and amount to approximately two euros per passenger kilometer.

The detailed overview of the parameters is shown in Table 10. In addition to the difference in profit, the pricing strategies of larger vehicles are particularly evident. Profit maximization is achieved with a low variable price of around one euro per passenger kilometer and a fixed price of around 12 euros per flight and passenger. The maximum range is not achieved by eVTOL vehicles k = 5 and k = 10. Despite the increased number of flights with larger eVTOL vehicles, a smaller fleet size is still used. This enables low maintenance costs.

For piloted eVTOL operations, the resulting total costs are shown in Fig. 10. Given the rather low salary of 50,000 € per year, profitable eVTOL configurations can only be found in two cases: k = 6 and k = 9. Within the decision variables, a higher pricing strategy is evident, with the fleet size initially remaining constant. This is reasoned as piloted eVTOL vehicles require a reduced vehicle payload and average load factor. As pilot salaries increase to 100,000 €per year, pricing strategies continue to increase, while fleet size decreases. If pilot crew costs further increase, operating the initially most profitable vehicle (k = 6) also becomes cost-inefficient. In summary, for piloted fleet operations, cost-efficiency can only be achieved under further assumptions of overall technological advances and optimistic cost estimates. For most vehicles, autonomous fleet operations are a substantial requirement in all parameter settings.

Table 10
Computed results for one operating day (base case parameters).

Parameter	Unit	eVTOL vehicle configuration k									
		1	2	3	4	5	6	7	8	9	10
Operational variables											
$fixprice$	€	12.08	13.49	11.56	13.26	11.81	13.48	12.85	13.34	12.89	12.96
$varprice$	€/pkm	1.09	1.18	1.18	1.17	1.31	0.95	1.05	1.05	1.01	1.04
v_{cruise}	€	50	54	36	50	32	88	60	66	68	36
$battery$	kg	100	120	70	190	400	360	260	410	440	130
$range$	km	95	95	95	94	95	95	95	95	95	23
$fleetsize$	–	103	121	102	84	53	53	59	47	44	82
UAM flights											
$distance$	10^3 km	690	568	623	577	519	797	701	689	739	475
Avg. flight	km	11.7	12.1	11.8	12.0	11.9	11.6	11.7	11.8	11.6	10.8
Financial metrics											
Revenue	10^3 €	132	117	121	118	107	152	135	135	141	96
TCO	10^3 €	110	116	111	116	113	108	111	113	109	106
Profit margin	€	16.8	0.71	8.2	1.9	−6.0	29.1	11.8	16.1	22.6	−10.0

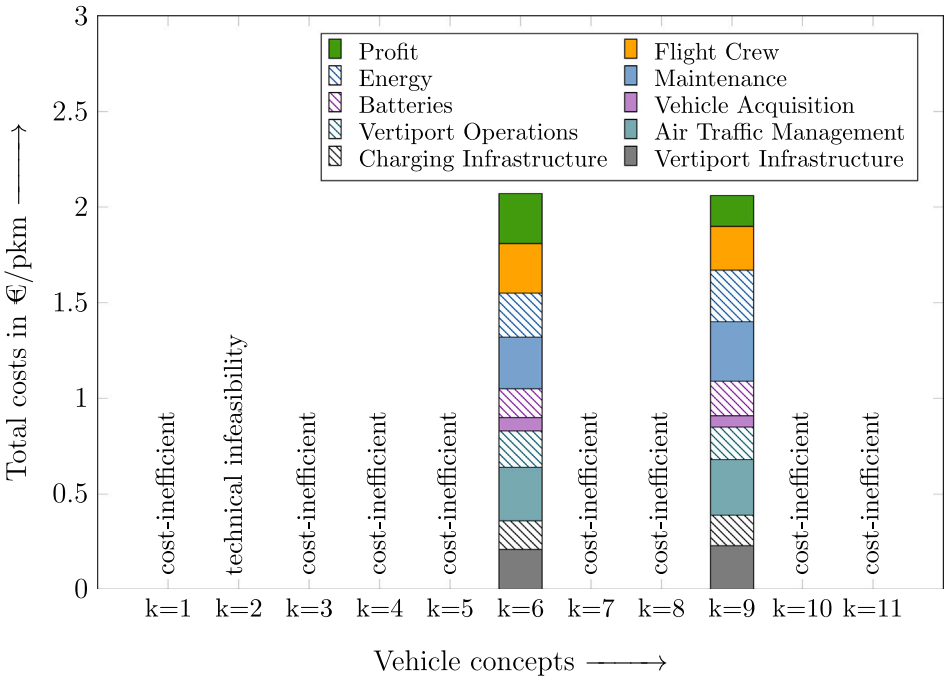


Fig. 10. Total costs for piloted eVTOL concepts.

5.3. Sensitivities

Sensitivities are examined in terms of production volume, technology-specific parameters, operational parameters, and cost parameters. Fig. 11 shows the sensitivities of the modeled eVTOL vehicles for varying production volumes. While a production volume of 500 vehicles per year represents a future scenario, 20 vehicles per year can be considered as initial phase for manufacturers. It can be stated that the lower number of units leads to an average five percent lower profit margin. In particular, eVTOL vehicles k = 2 and k = 4 are unprofitable at the fleet level for low production volumes. Increased production and ramp-up strategies are therefore particularly relevant for small eVTOL vehicles.

Operational sensitivities are shown in Fig. 12 for the base case of vehicle k = 6 and an annual production volume of 20 eVTOL vehicles. Reference TCO and profit data are displayed in solid colors. In terms of operating days, daily profits increase by an average of 240 euros per additional operating day. Revenue remains relatively constant. The percentage scaling of the UAM simulation leads to an average daily profit increase of 820 euros per percentage increase. Revenue also increases as the fleet size and all other associated costs scale accordingly. Ticket prices remain relatively constant. With regard to load factor and process times, it can be drawn that an increase in the average load factor at the operational level is associated with an increase in process times, as more passengers have to be pooled efficiently. A further comparison of these parameters shows that extending vertiport waiting times by 2 min to collect additional passengers, that arrive with the same destination, is only profitable if the load factor increase by at least 0.1 passengers per flight. This represents a relevant reference value for future operations research models and dial-a-flight models.

In addition, the sensitivities to battery technology are analyzed. With respect to the total cost model, both battery efficiency and battery-specific energy density can vary for initial and future UAM scenarios. This is particularly relevant for eVTOL vehicles with high MTOM. Fig. 13 shows the sensitivities for eVTOL vehicle k = 8. It is found that initial battery technologies are likely to be cost-inefficient, whereas an increase in energy density over 300 Wh/kg and a battery efficiency over 75% can enable profitable operations. The influence of both parameters on the overall profit is comparable, as the total battery mass can be reduced and the range increases. A similar trend can be seen for the other eVTOL vehicle concepts, with vehicles k = 6 and k = 9 being

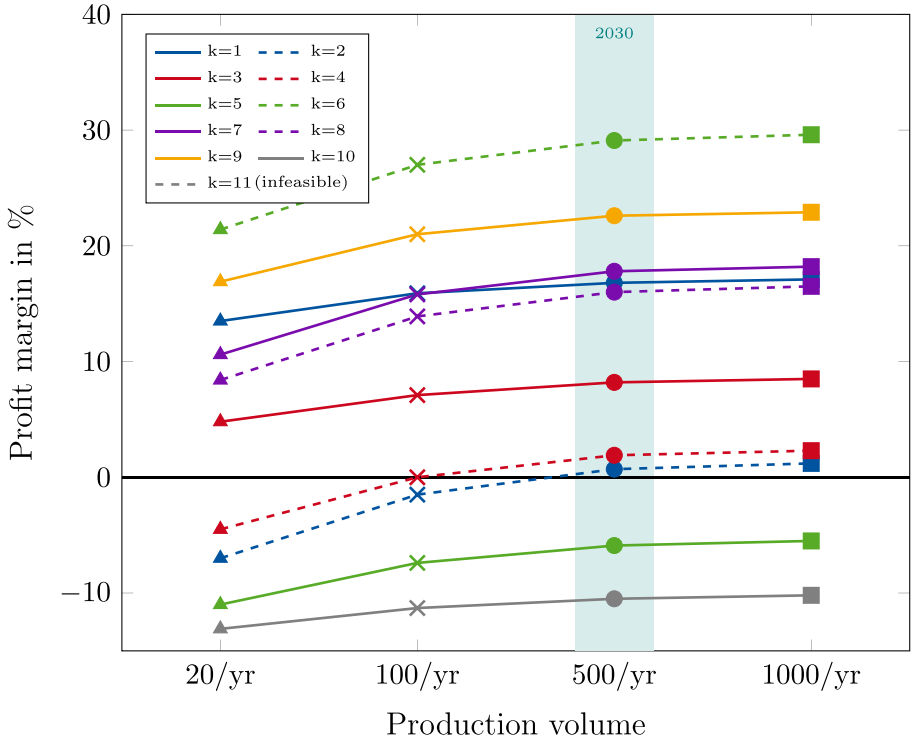


Fig. 11. Profit margin for different eVTOL vehicle acquisition prices.

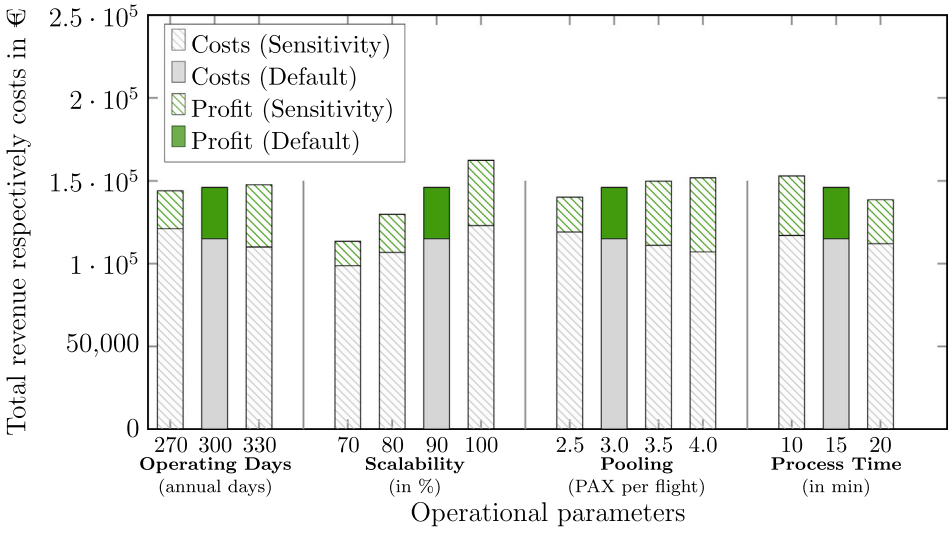


Fig. 12. Operational sensitivities for k = 6 with an annual production volume of 20.

more robust to technological developments due to their initially higher profit margins.

Cost sensitivities are shown in Fig. 14. Results indicate that a variation in battery prices and costs for the air traffic management system only affect total costs, while revenue remains constant. Variations in maintenance costs result in both a reduction in revenue and an increase in total costs. This is reasoned as the eVTOL fleet size is coupled with maintenance costs, so that the total UAM demand is reduced. The same applies for annual vertiport costs. It should be noted that maintenance costs are even more sensitive for smaller eVTOL vehicles up to four passengers, resulting in cost-inefficient operations for upper limit settings.

6. Discussion

The studies carried out allow a discussion in three aspects, namely eVTOL production, cost-efficient UAM operation and sensitivities:

- Although a validation of the introduced and analyzed production cost model extension is not yet fully possible due to currently little reference data, the results are reasonable and consistent with known cost shares, available reference points, and sensitivities. While our DAPCA-based approach represents a first-order approximation for eVTOL production costs adapted from fixed-wing aircraft relationships, the transparent framework including production volumes enables future recalibration as eVTOL specific manufacturing data becomes available. The model also shows

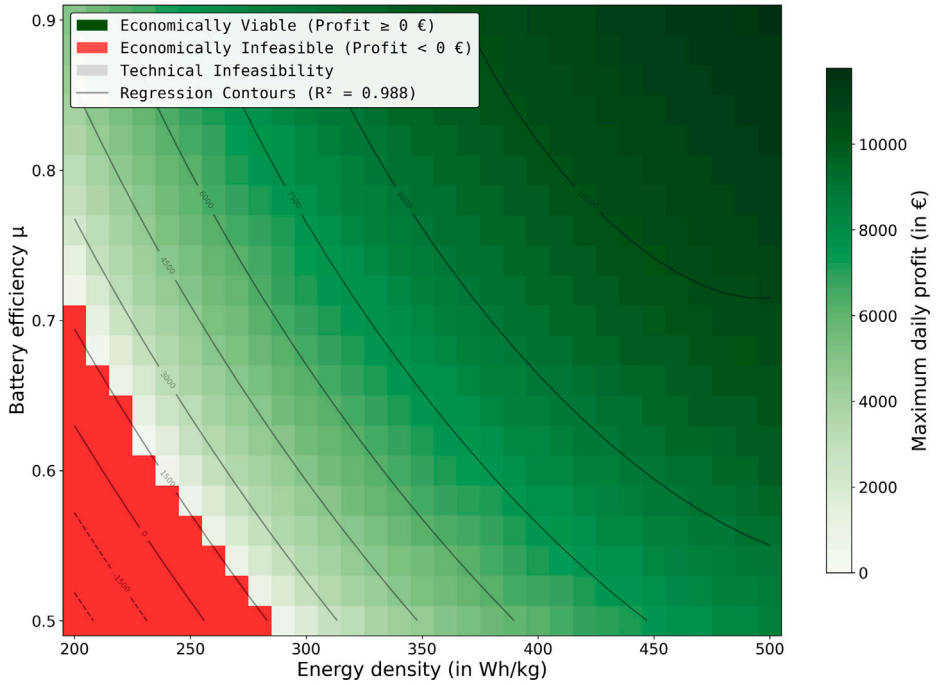


Fig. 13. Battery specific sensitivities for eVTOL vehicle k = 8.

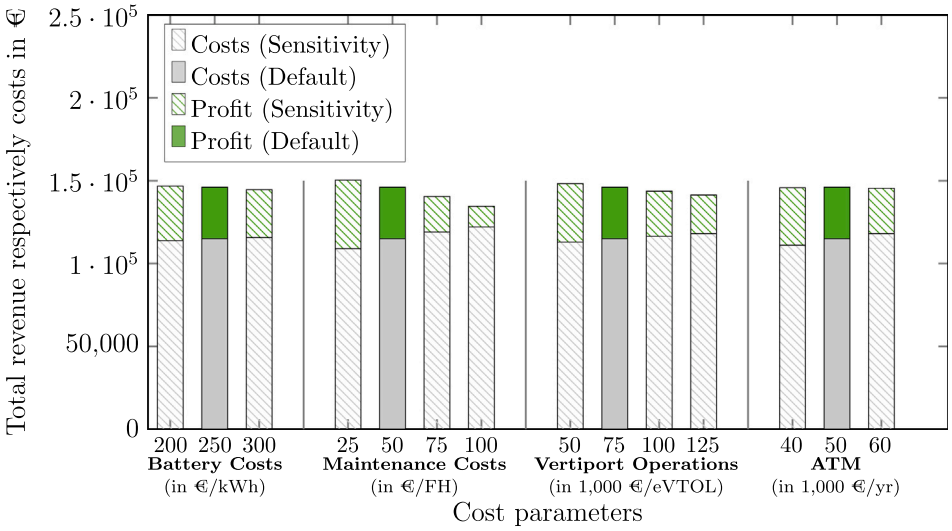


Fig. 14. Cost sensitivities for k = 6 with an annual production volume of 20.

good qualitative and quantitative agreement with previous research, both for the base case with a medium number of vehicles produced annually and for scenarios with smaller production volumes. Based on Figs. 5 and 6, the plausibility of the model can be assessed. Additionally, the model offers a high degree of complexity and hence allows flexibility for future adjustments based on published data, enabling the derivation of configuration-specific surrogate models. There is an overall profit increase of five percent between initial production volume and future production in 2030, with particular relevance for small eVTOL vehicles. Consequently, a ramp-up strategy could be supported both from a governmental perspective and through synergies between different eVTOL manufacturers and supply chains. The necessary increases in production volumes are already being pursued by eVTOL companies, but are dependent on investments in infrastructure to enable UAM fleet operations.

- The overall cost and profit analysis on fleet level indicates profitable UAM operations for future technology assumptions and autonomous flight operations. The modeled eVTOL vehicle configurations perform differently in terms of cost-efficiency. Most relevant, larger eVTOL vehicles allow lower total costs due to smaller required fleet sizes. Also, Multicopter configurations are less profitable even in optimistic parameter settings as high ranges cannot be realized while allowing energy-efficiency. Based on the overall evaluation in Fig. 9 and Table 10, ticket prices are relatively robust and sum up to average ticket prices of two euros per passenger kilometer. These corresponding costs align with recent UAM cost studies, which state that costs per passenger kilometer range from 1.20 € to 3 € depending on operational scenarios and optimization strategies (Goyal et al., 2018; Holden & Goel, 2016; Husemann et al., 2024; Kirste & Stumpf, 2024; Pak et al., 2024). Our estimates fall within the lower range of this spectrum

for energy-efficient eVTOL designs, fully autonomous operations, advanced 2030 battery technology, and demand-responsive fleet sizes. High flight speeds can increase profit due to the potential to further reduce travel times, making air traffic management even more relevant in the context of future autonomous flight operations of eVTOL fleets. Total UAM trip requests in the Rhine–Ruhr case study scenario are short distances, with maximum travel distances also being requested which determines the eVTOL vehicle sizing of battery masses, range, and cruise speed. Despite finding profitable study instances for future parameter settings, cost-efficiency alone will not enable UAM operations in the near future. Acceptance, air traffic management of autonomous vehicles and noise regulations within urban areas have to be addressed by all UAM stakeholders.

- Operational sensitivities indicate the number of annual operating days and the vehicle load factor as relevant parameters to address. The latter contrasts with short process times at the vertiports. Passenger pooling sensitivities reveal that extending vertiport waiting times by 2 min to collect additional passengers is only profitable if the average load factor increases by at least 0.1 passengers per flight. This trade-off between waiting time and vehicle utilization is critical for fleet dispatching optimization. Battery sensitivities confirm the relevance of future improvements in battery specific energy density of the battery packs. Further sensitivities with regard to composite material production result from the initial modeling approach as series production. The correlations at operational fleet level clearly indicate fully composite eVTOL vehicle designs for cost-efficiency. The model factors are evaluated on the basis of the configuration specific analyses. Here, the influence of the maximum cruise speed could be adjusted configuration specifically and the influence of flight test operations with increasing technological maturity of both autonomous vehicles and UAM services could motivate cost model adjustments in the future.

7. Conclusion

This paper analyzes total costs of different eVTOL concepts on vehicle level as well as on operational fleet level. First, a model extension for development and production cost modeling is performed based on a comprehensive literature review. In particular, this includes the modeling of Multicopter, Lift + Cruise, and Tilt-X configurations, whereby reference sizing is taken into account for comparability. UAM adjusted airframe costs are derived as a function of established cost calculations for small aircraft. Propulsion and avionic costs are also modeled configuration specific. Linearizations are extended by economies of scale. The Total Cost of Ownership model on the fleet level incorporates costs for infrastructure, recharging, air traffic management, vertiport operations, vehicle acquisition, battery replacements, maintenance, and energy. The evaluation is carried out as a case study of the metropolitan region Rhine–Ruhr, using agent-based simulation data.

The study provides new insights into cost and profit sensitivities. The production costs for eVTOL vehicles vary significantly depending on production volume and vehicle configuration. Smaller eVTOL vehicles require a higher production volume to be cost-efficient, while larger vehicles benefit from smaller fleet sizes. Autonomous flight operations and larger eVTOL vehicle configurations enable lower total costs due to reduced maintenance and operating costs at the vertiports. Ticket prices for maximum profits are relatively robust at around two euros per passenger kilometer comprising a base fare with a variable price. Sensitivity analyses show that the number of operating days per year and the vehicle load factor are key parameters for maximizing profit. Increasing the average passenger pooling factor by 0.1 within two minutes would further increase profits. Improvements in battery technologies are critical to the profitability of eVTOL vehicles with high Maximum Take-Off Mass. Vehicle configurations entirely made from composite materials show highest profit margin potential, whereas aluminum and hybrid concepts are outperformed due to resized propulsion systems and the snowball effect of additional energy consumption.

The results motivate an application of the total costs model in ongoing and follow-up research. This also includes different study regions as well as parameter scaling for enhanced modeling of boundary conditions in the overall design space. Linearized empty mass dependent surrogate models allow application in other UAM studies without full model implementation. Future calibration of the production cost model with additional available data points could improve accuracy. As eVTOL manufacturers transition to series production, detailed cost estimates for eVTOL configurations could extend the current adaptations from fixed-wing aircraft data. UTM and insurance cost extensions could improve evaluation of modeled profit margins and sensitivities. Moreover, the cost optimization of eVTOL vehicle designs and UAM services based on the introduced model is a promising research direction to profitably integrate UAM in the overall mobility network.

CRediT authorship contribution statement

Ansgar Kirste: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Eike Stumpf:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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