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Possibility-based Sizing Method for Hybrid Electric Aircraft

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ABSTRACT At the early stage of aircraft design, the sizing process plays a critical role in determining key parameters such as mass, geometry, and propulsion system characteristics based on design requirements. However, existing sizing methods, relying on historical data, assumptions, and low-fidelity models, often fail to address uncertainties, leading to costly design modifications, particularly for electric aircraft, where technological uncertainties pose significant challenges. It is crucial to account for uncertainties at the sizing stage to ensure reliable outcomes, highlighting the need for a method that efficiently integrates uncertainty into the process. We propose a possibility-based sizing approach, which accounts for design uncertainties into sizing process, yields possible feasible design outcomes and identifies critical parameters for refinement in later stages. We verified our approach with two case studies meeting CS23 certification. The results demonstrate design feasibility through trade-offs between conservative and optimistic designs, with possibility indices from 0.75 to 1, identifying maximum and stall speeds as key limiting factors. Sensitivity analysis shows that aerodynamic design, airframe, and propulsion efficiencies significantly impact maximum takeoff mass. Propulsion system integration achieves a relative mass reduction of 0.05, outperforming hydrogen fuel cells (0.025) and battery systems (0.009). The study highlights that power density is more critical than battery energy density in high-power segments, providing valuable insights for sizing and key parameters in future hybrid electric aircraft development.

INDEX TERMS Hybrid electric aircraft, Sizing, Design under uncertainty, Possibility-based design optimization, Battery and Hydrogen fuel cell.

I. INTRODUCTION

ELECTRIC aircraft have gained significant interest in the aerospace industry due to their potential to lower carbon emissions, reduce acoustic noise, increase energy efficiency, and lower operating costs compared to conventional jet-fuel-powered aircraft [1]. However, such aircraft face flight endurance and range limitations compared to internal combustion engine (ICE) aircraft. To address these limitations, hybrid electric propulsion, which combines an electric powertrain with a conventional combustion engine, is emerging as a practical solution [2]. Furthermore, the integration of fuel cells and batteries in hybrid electric propulsion systems has shown promise [3], presenting a compelling strategy for sustainable aviation.

At the beginning of the aircraft design process, initial sizing is conducted based on selected concepts and assumed analysis parameters. This process determines key characteristics such as mass, configuration, and propulsion system attributes while ensuring performance and mission requirements are met. Once the aircraft is sized, the design undergoes more detailed evaluations, and necessary revisions are made. Thus, sizing is a crucial step in the design process. The retrofitting of electric propulsion systems onto existing aircraft has been extensively researched, with various electric aircraft sizing methods proposed by researchers. For example, [4], [2], and [5] developed initial sizing methods for hybrid electric aircraft and distributed electric propulsion. Similarly, [6] proposed sizing methods for hybrid powertrains, while [7] investigated the sizing and mass estimation of hydrogen fuel cell and battery-powered aircraft.

However, the electrification of aircraft exhibits significant variations, heavily influenced by design parameters such as assumptions regarding batteries, hydrogen fuel cells, and electric motor power density, depending on the entry into service (EIS) year. Therefore, the sensitivity of these parameters is studied after the aircraft is sized. [8] explored a 50-passenger hybrid electric aircraft, analyzing the influence of technology on the aircraft's performance. [9] conducted a system-level trade-off study for a hybrid parallel propulsion architecture targeting an EIS in 2030. [10] presented a method to identify potential aircraft designs with electrified powertrains, considering EIS scenarios in 2025 and 2050. [11] investigated feasible designs for electric aircraft across different mission ranges, accounting for variations in technological levels. [12] studied the performance of hydrogen-fueled aircraft with potential advances in hydrogen tank gravimetric indices and reductions in aircraft mass fractions between 2020 and 2050.

Most articles referenced above adopt varying technological assumptions, introducing different assumption values depending on the projected year. This variability introduces uncertainty into the design of novel aircraft, often leading to violations of the design constraints. Significant research has focused on design-under-uncertainty approaches for electric aircraft design. For instance, [13] examines the uncertain parameters of electric propulsion that impact hybrid-electric aircraft performance. Departing from traditional methods, [14] introduces a novel approach to evaluating aircraft concepts using a credibility-based criterion. Building on this, [15] explores the scalability of hybrid-electric technology across different aircraft classes using this credibility-based MDO framework.

These papers, which study design under uncertainty in electric propulsion technologies, often rely on inaccurate probability distributions. As a result, the propagation of uncertain parameters can lead to unreliable design outcomes, frequently causing violations of constraints in novel designs. Moreover, existing sizing methods on hybrid electric aircraft, as mentioned earlier, heavily depend on historical data, empirical methods, and assumed values, which introduce significant uncertainty in later design stages. Therefore, after sizing, sensitivity analysis is performed based on the assumed parameters to account for uncertainty, often resulting in under-designed or over-designed systems that violate design constraints. Consequently, numerous time-consuming iterations are required to achieve a feasible preliminary design, particularly for hybrid electric aircraft. This underscores the need for effective management of these uncertainties during the early stages of design to enable more reliable design decisions. To the best of our knowledge, no sizing method at the early design stage adequately addresses these challenges.

To address these challenges, a new sizing approach is essential to mitigate uncertainties arising from both analysis and technology. This approach should not only focus on vehicle sizing and parameter sensitivity but also seamlessly integrate design uncertainties, particularly those related to electric propulsion systems, into the sizing process. This integration requires a reliable sizing method, design optimization under uncertainty, and uncertainty modeling with insufficient data. Such an approach allows for an efficient design process, enabling designers to identify potential feasible sizing results and critical parameters that need to be addressed in later stages of the design process.

We present a possibility-based sizing approach that integrates our deterministic sizing method for hybrid-electric aircraft, validated through existing literature, with Possibility-Based Design Optimization (PBDO). This approach provides a comprehensive understanding of the complex relationships between design parameters and system performance. By incorporating a fuzzy membership function into an uncertainty model alongside the PBDO optimizer, this method effectively addresses challenges arising from insufficient data. Through this integration, we aim to identify potentially feasible design solutions, balancing optimistic and conservative designs that meet specified requirements while accounting for the importance of each uncertain parameter within design constraints. This innovative method seeks to enhance reliable sizing decisions for hybrid electric aircraft by addressing critical parameters across various design uncertainties, including those related to electric propulsion.

This article is structured as follows: Section II introduces fuzzy membership functions and PBDO. Section III presents the paper's motivation. Section IV details the proposed method. Section V covers the hybrid electric aircraft sizing methodology, and Section VI discusses the validation process. Section VII presents a case study, while Section VIII discusses the findings and critical parameters for further development. Finally, Section IX provides conclusions, limitations, and future research recommendations.

This study focuses on regional aircraft utilizing hydrogen fuel cells and batteries as an energy system to meet CS23 certification requirements. Throughout the paper, we refer to these aircraft as Hybrid Electric Aircraft with Hydrogen Fuel Cells and Batteries (HEA-H2B).

II. FUZZY MEMBERSHIP FUNCTION AND PBDO THEORY

To provide context for our proposed method, this section presents the foundational theory of fuzzy membership functions for uncertainty modeling, the core principles of possibility based design optimization (PBDO).

A. FUZZY MEMBERSHIP FUNCTION

Fuzzy sets can be used to modeled as uncertain parameters when data is insufficient by constructing the membership function [16]. Fuzzy sets use membership functions to describe the degree of membership. The possibility index α governs the uncertainty interval. A triangular function is defined by the maximum interval width, which linearly decreases as α approaches unity [17]. These functions are modeled based on experts' knowledge. A fuzzy membership function (Π_x) is a bounded function that varies between 0 and 1, shown in (1).

$$0 \leq \Pi_x(x) \leq 1 \tag{1}$$

where $\Pi_x(x)$ represents the degree of membership observed within a given interval. A fuzzy membership function and the interval of the possibility index α, providing the confidence interval $[x_L^\alpha; x_R^\alpha]$ for uncertain parameters with bounds $[x_{lb}; x_{ub}]$, are shown in Fig. 1.

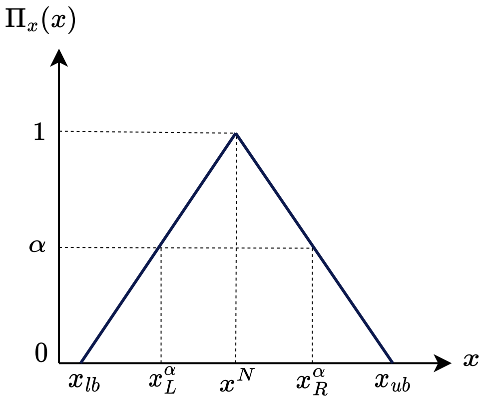

FIGURE 1. Triangular fuzzy membership function

B. POSSIBILITY-BASED DESIGN OPTIMIZATION

PBDO aims to find the possible combinations of uncertain variables and parameters within the fuzzy interval that will not violate any of the given constraints and to obtain the most probable points (MPP), which is crucial for pinpointing the limiting state of constraints attributed to uncertain parameters and variables. The fuzzy interval for each uncertain design variable or parameter is defined through a membership function, as shown in Fig. 1. The PBDO optimization can be formulated as

$$\begin{aligned} \min_{d,x} \quad & f(d, \bar{x}, \bar{p}) \\ \text{s.t.} \quad & \Pi(g_i(\mathbf{d}, x, p) > 0) \leq \alpha_t, \; i = 1, 2, \cdots, n_p \\ & d^{lb} \leq d \leq d^{ub} \\ & x^{lb} \leq x \leq x^{ub} \end{aligned} \tag{2}$$

where d is the vector of the deterministic design variables, $\mathbf{x} \in \mathbf{R}^{n_x}$ is the vector of the uncertain (fuzzy) design variables, having a membership function $\Pi_{x_i}(x_i)$, and $\mathbf{p} \in \mathbf{R}^{n_p}$ is the vector of the uncertain parameter. $\bar{x}$ and $\bar{p}$ are vectors of the uncertain design variables' and parameters' mean values, respectively. Having a membership function, α_t is the target possibility index, and n_d, n_x and n_p are several deterministic variables, uncertain variables, and uncertain parameters respectively. An example of PBDO optimum is explain in Section. III.

III. CONCEPTUAL BASIS OF THE METHODOLOGY

The PBDO method, as depicted in Fig. 2, is an effective strategy for managing uncertainty in design optimization. While deterministic optimization is traditionally favored due to its predictability, PBDO offers a practical alternative in uncertain scenarios. A trade-off scenario between a deterministic design variable (d) and an uncertain parameter (p_1) is shown. Assuming the deterministic optimum point aligns with the constraint (g_2), adjustments in the exact value of (d) optimize the objective function while ensuring feasibility across any value of (p_1) within the uncertain interval. The width of these uncertainty intervals is regulated by a fuzzy membership function and (α_t), facilitating the identification of the most probable point (MPP) within the interval, while satisfying the design constraints. This is crucial for pinpointing the limiting state of constraints attributed to uncertain parameters. The MPPs are the critical parameters for which the design could fail for the possible sizing results.

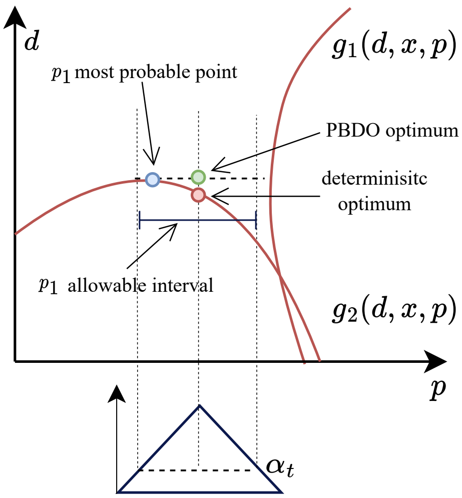

FIGURE 2. Tradeoffs of PBDO design with deterministic design variable (*d*) and one uncertain parameter (*p*), inspired from [17]

The evaluation of critical parameters is of significant importance to this method and is closely tied to the outcomes of the PBDO optimization. Following the completion of the PBDO optimization, active constraints can be identified when $(g(d, x, p) = 0)$, while the PBDO also provides access to the MPPs of the uncertain parameters, defining the critical conditions where the design constraints are meet. Parameters adhere to allowable tolerances that align with the design constraints, with α_t guiding the permissible range of the parameters. The MPPs are pivotal loci where the probability density function reaches its maximum value at the probabilistic constraint [18], representing the point closest to the constraint boundary within the specified uncertain interval.

By utilizing the PBDO optimization strategy and MPP concepts, this paper seeks to surpass existing sizing methods by exploring feasible sizing outcomes and identifying critical parameters for electric aircraft design. These parameters can be addressed in subsequent design stages. Fig. 2 illustrates the exploration of potential aircraft sizes across various probability indices, ranging from optimistic to conservative designs, while highlighting the MPPs of each constraint. These MPPs offer valuable insights into critical parameters essential for the mature design phase, accounting for design uncertainties. This approach promotes more reliable sizing decisions and strengthens the overall design process.

IV. METHODOLOGY

This section presents a possibility-based sizing approach to identify potential feasible designs and critical parameters for hybrid electric aircraft by considering various sources of uncertainty. Fig. 3 depicts the framework, which provides a comprehensive approach by combining the hybrid electric aircraft sizing method with design under uncertainty. This methodology ensures that an aircraft size meets all specified constraints, even when the uncertain parameters vary within their uncertainty bounds by possibility indices. Additionally, it facilitates the determination of the critical combination of uncertain parameters for each design constraint and the sensitivity of the constraint at a given critical point.

Firstly, we develop a sizing method for hybrid electric aircraft to estimate the size of the aircraft, including the power-to-weight ratio, wing loading, performance, and mass, tailored to meet specific design requirements dictated by the mission profile. The method for this detailed analysis is elucidated in Section V.

Secondly, we meticulously gather the parameters that influence this sizing method, including aerodynamic coefficients, mass fractions, and electric propulsion technology parameters, from various reliable sources such as academic literature, research papers, and historical data. These diverse data sets are then compiled into a comprehensive database. Subsequently, we employ this compiled data to model the uncertain parameters, generating fuzzy membership functions for each parameter. This modeling approach proves invaluable in integrating uncertain parameters into the design optimization process.

Next, a design under uncertainty is executed using a PBDO optimizer alongside the developed sizing method, integrating the design requirements, mission profiles, and target possibility indices α_t while factoring in the uncertain parameters derived from the fuzzy membership functions. In this proposed sizing method, the design requirements are integral to the constraint functions, and the definitions of $g(d,x,p)$ and $f(d,\bar{x},\bar{p})$ are explained in Section II-B. Feasible aircraft sizes for each possibility target are obtained from the design under uncertainty module, ensuring that the design constraints are satisfied despite variations in the uncertain parameters.

In addition, by leveraging the advantage of the PBDO optimizer, the active probabilistic constraints and the uncertain parameters at the most probable point of failure (MPP) are initially evaluated. Leveraging the uncertain parameters at the most probable point allows for identifying the limiting parameters for each probabilistic constraint. Subsequently, a sensitivity analysis assesses the critical parameters constrained by the design requirements. Based on the outcomes of the sensitivity analysis, qualitative discussions are undertaken for each critical parameter and design requirement, facilitating informed decisions for the subsequent design process and the future development of novel HEA-H2B designs.

A. DESIGN UNDER UNCERTAINTIES

1) Uncertainty Modeling: Create Fuzzy Function

This paper uses historical data as a repository of expert knowledge to facilitate the effective modeling of uncertainties via triangular fuzzy membership functions. It is worth noting that historical datasets, including parameters related to aerodynamic coefficients, mass fractions, and propeller efficiencies, are compiled from reputable sources in the academic literature. Statistical descriptors such as the mean, upper limit, and lower limit are derived from histograms. This approach fosters a comprehensive understanding of the characteristics of the data distribution for considering uncertainty in the early design of aircraft. The uncertainty surrounding electric propulsion technology parameters, including efficiency, power density, and energy density, necessitates a systematic approach to incorporating technology roadmap assumptions derived from various sources in the literature. These assumptions, aligned with projection years, are meticulously cataloged in a centralized database, facilitating the development of a confidence interval regression model to ascertain the uncertainty bounds for each parameter. Notably, a 95% confidence interval (CI) is employed to establish the lower and upper limits of the fuzzy interval.

2) PBDO Solver

In this paper, we employ our in-house PBDO optimizer, which utilizes the performance measure approach (PMA) [19] to find the most probable point (MPP) and adopts a sequential approach to solve optimization problems. The in-house PBDO optimizer has been validated and successfully applied to various aircraft design problems [16], [17], [20]. While the theoretical implementation of the PBDO optimization and fuzzy triangular function modeling methods has been verified in our code, this paper focuses on proposing a new sizing approach that leverages the strengths of PBDO. Consequently, we have limited the theoretical proofs of PBDO in this work.

3) Sensitivity Analysis

A sensitivity analysis is conducted at the MPP of each constraint to assess the significance of each uncertain parameter based on the PBDO results. The relative change for each design constraint at the MPP and the optimum design condition is calculated using (3), with the optimum design condition characterized by the highest probability density at the limiting state of the corresponding constraints.

$$\Delta g_{i_{relative}}\big|_{(d^*,x^*,p_{MPP_i})} = \frac{g(\Delta p_{MPP_i}) - g(p_{MPP_i})}{g(p_{MPP_i})} \tag{3}$$

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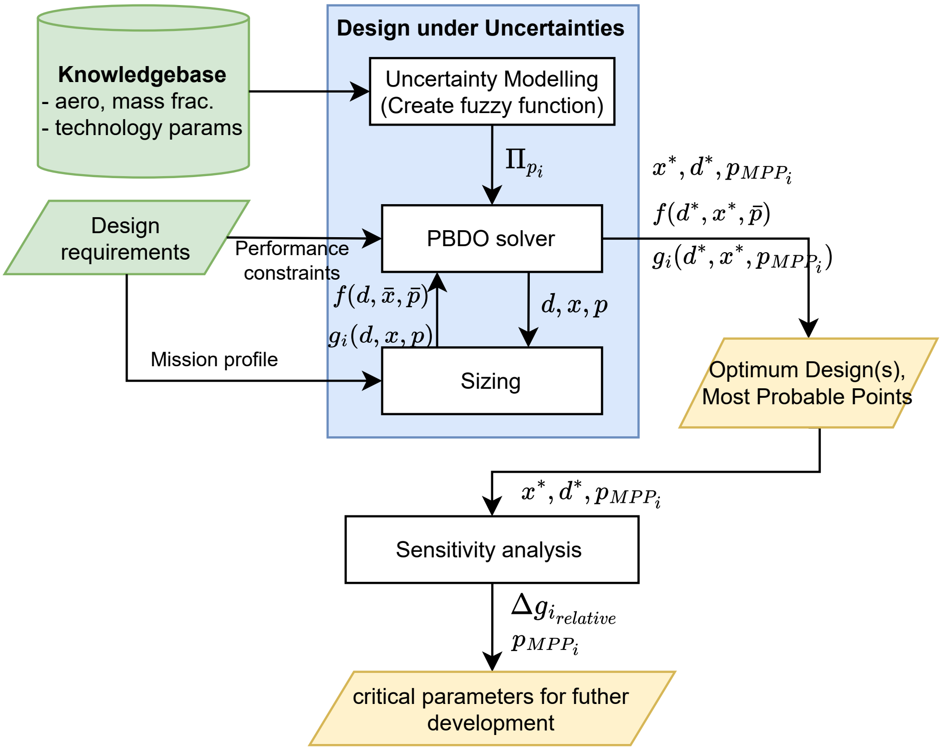

FIGURE 3. Possibility-based Sizing Method for Hybrid Electric Aircraft

V. SIZING METHODOLOGY FOR A HYBRID ELECTRIC AIRCRAFT

Sizing a novel aircraft involves determining the propulsion size, wing area, and maximum takeoff mass to meet the design requirements. The developed method, based on textbooks and papers from the literature, is illustrated in Fig. 4 and consists of seven main modules: aerodynamics, performance analysis, propulsion system mass calculation, mission analysis, energy system mass calculation, maximum takeoff mass calculation, and optimization to determine wing loading (W/S) and power-to-weight ratio (P/W). This study employs the PBDO optimizer to identify the optimal solutions.

The Configuration/Aerodynamics module takes the input assumption parameters and wing loading (W/S) to estimate the wing area (S_w), wing span (b), and aerodynamic coefficients, including the induced factor (k), zero-lift drag coefficient (C_{D_0}), and maximum lift coefficient ($C_{L_{\max}}$). A simplified drag polar and linear maximum lift coefficient calculation are used. The values of (C_{D_0}) and (C_L) for takeoff conditions are estimated by considering the increase in drag due to landing gear and flap deflection, represented by ($\Delta C_{D_{0_{\text{flap}}}}$) and ($\Delta C_{L_{\text{flap}}}$) from [21]. Point performance and field performance are analyzed by solving the general equations of motion for steady-level flight, climb, descent, and takeoff conditions. This analysis calculates key parameters such as the maximum rate of climb ($ROC_{\max}$), one-engine-inoperative climb gradient (G_{OEI}), service ceiling ($h_{ceiling}$), stall speed (V_{stall}), maximum speed (V_{max}), takeoff length (S_{TO}), and other important parameters using methods from [21]–[23].

A linear approximation of the powertrain used in this method is illustrated in Fig. 5. The energy system includes the battery, fuel cell, and hydrogen tank, while the propulsion system consists of the propeller, motor, and motor control unit (MCU). The hybridization parameter (H_P), which represents the ratio of battery power to total power, is introduced for the hybrid propulsion system.

$$H_P = \frac{P_{\text{batt}}}{P_{\text{total}}} = \frac{P_{\text{batt}}}{P_{\text{batt}} + P_{\text{FC}}} \tag{4}$$

The power of each component can be calculated by multiplying the power-to-weight ratio with the maximum takeoff mass input and the related component efficiencies. Battery and fuel cell power are estimated using the hybridization factor in (6) and (7).

$$P_{\text{total}_{\text{elec}}} = n_{\text{motor}} \cdot P_{\text{MCU}} \tag{5}$$

$$P_{\text{batt}} = H_P \cdot P_{\text{total}_{\text{elec}}} \tag{6}$$

$$P_{\text{FC}} = (1 - H_P) \cdot P_{\text{total}_{\text{elec}}} \tag{7}$$

The estimation of the mass of the propulsion system includes the propeller, motor, and MCUs. The mass of the propeller is calculated based on Raymer [23] using (8). The mass of each component is obtained based on the power density (P^*) and efficiency (η) of each electronic component,

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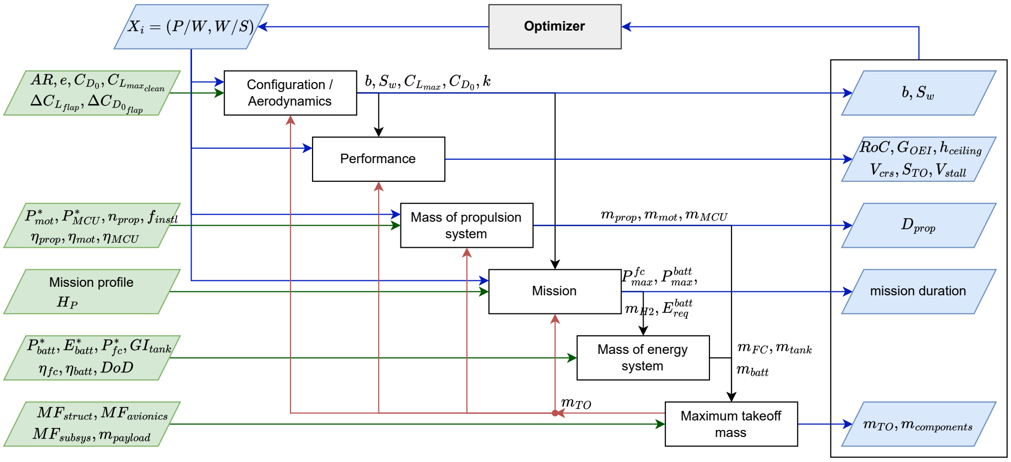

FIGURE 4. Sizing method for hybrid electric aircraft

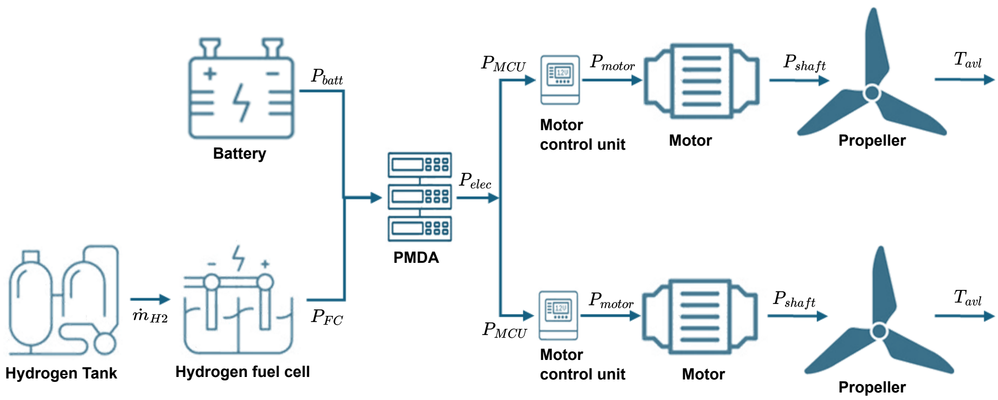

FIGURE 5. Schematic diagram of the hybrid powertrain

which are determined by the level of technology from input parameters using (9).

$$m_{\text{prop}} = 1.1 \cdot (D_{\text{prop}} \cdot P_{\text{motor}} \sqrt{N_b})^{0.52} \tag{8}$$

$$m_{\text{motor/MCU/batt/FC}} = P_{\text{Motor/MCU/batt/FC}} \cdot \frac{1}{P^*_{\text{Motor/MCU/batt/FC}}} \tag{9}$$

The total mass of the electric propulsion system is calculated by taking into account the installation factor (f_{install}), typically ranging from 1.05 to 1.3 [24], as shown in (10).

$$m_{\text{propulsion}} = f_{\text{install}} \cdot n_{\text{prop}} \cdot (m_{\text{prop}} + m_{\text{motor}} + m_{\text{MCU}}) \tag{10}$$

Mission analysis is conducted to estimate the energy required, fuel consumption, and maximum power for the hydrogen fuel cell and battery, allowing for the estimation of the energy sources' masses based on the input mission profile and hybridization factor. The power required for each mission segment is determined using the motion equations for the takeoff, climbing, cruising, and loitering phases.

$$E_{\text{batt}} = \sum_{i=1}^{n} \frac{P_{\text{batt}_i}}{\eta_{\text{batt}}} \cdot t_i, \quad \forall i \in N \tag{11}$$

Here, (i) denotes the mission segment belonging to the mission profile (N). The energy required for the battery and fuel cells can be estimated by summing the energy of each flight mission from (11). The hydrogen fuel required for the mission can be calculated by summing the fuel consumption for each mission segment (13).

$$\dot{m}_{\text{H2}} = \frac{P_{\text{FC}}}{LHV \cdot \eta_{\text{FC}}} \tag{12}$$

Here, (P_{FC}) is the required electrical power of the fuel cell. LHV is the low heating value of hydrogen, which is 33.33 kWh/kg, and (η_{FC}) is the efficiency of the fuel cell. The total fuel mass can be calculated by multiplying the mission time by the fuel consumption for each segment, as given in (12).

$$m_{\text{H2}} = \sum_{i=1}^{n} \dot{m}_{\text{H2}_i} \cdot t_i, \quad \forall i \in N \tag{13}$$

The sizing of the energy systems is essential for hybrid-electric aircraft. In this method, the battery and hydrogen fuel cell are connected in parallel, as shown in Fig. 5, and the masses of the battery, hydrogen fuel cell, and hydrogen tank are calculated in this module.

The battery is sized based on both the power and the energy required from mission analysis; the maximum mass is considered to ensure it is not undersized, using (14). The battery mass from power density ($m_{\text{batt}_{P*}}$) is estimated using (9).

$$m_{\text{batt}} = \max\{m_{\text{batt}_{P*}}, m_{\text{batt}_{E*}}\} \tag{14}$$

$$m_{\text{batt}_{E*}} = \frac{E_{\text{batt}}}{DoD \cdot E^*} \tag{15}$$

Here, (E_{batt}) is the energy required for the mission, calculated based on the conditions of the mission. (DoD) represents the depth of discharge for the battery pack, (η_{batt}) is the efficiency of the battery, and (E^*) is the battery's specific energy density. The fuel cell and hydrogen tank are sized based on the power density (P^*_{FC}) and the tank gravimetric index (GI). The mass of the hydrogen fuel cell energy system is estimated using (9) and (16).

$$m_{\text{tank}} = m_{\text{H2}} \cdot \left(\frac{1}{GI} - 1\right) \tag{16}$$

The total energy system mass (m_{energy}) can be calculated by summing the mass of the battery (m_{batt}), fuel cell (m_{FC}), hydrogen mass (m_{H2}), and tank mass (m_{tank}).

The maximum takeoff mass (m_{TO}) is finally calculated by using the resulting propulsion system mass ($m_{\text{propulsion}}$) and energy system mass (m_{energy}) from (17). The method uses the mass fraction value for structural (MF_{struct}), avionics (MF_{avis}), and subsystems (MF_{subsys}) to calculate the airframe mass.

$$m_{TO} = \frac{m_{\text{propulsion}} + m_{\text{energy}} + m_{\text{payload}}}{1 - (MF_{\text{struct}} + MF_{\text{avi}} + MF_{\text{subsys}})} \tag{17}$$

Each analysis module's calculated mass is updated until the mass converges using the fixed-point iteration method.

VI. VALIDATION OF SIZING METHOD

A validation of the sizing method is conducted for the battery energy systems using the open literature of [25], which validated the hybrid electric aircraft sizing method developed at FH Aachen (method A) and TU Delft (method B). The analysis of an aircraft's hydrogen fuel cell energy system is also validated by the analysis method of [26], which retrofits the Dornier 228NG to a hydrogen fuel cell energy system. The input parameters of the mission profile, payload mass, aerodynamics assumptions, efficiency assumptions, and power density values are the same as those in the referenced paper. The power-to-weight ratio, wing loading, structural mass, motor mass, battery mass, and tank mass are validated and shown in Table 1 and Table 2. The validation results show that the sizing for an aircraft with a battery energy system found a higher percentage difference of $+6.313\%$ and $+4.225\%$ for the battery mass for the FH Aachen and TU Delft methods [25], respectively. The validation of the sizing for a hydrogen fuel cell energy system, in Table 2, shows that the highest percentage difference is found in the fuel tank mass, -8.477%, indicating that our developed sizing method aligns with the reference method of [26].

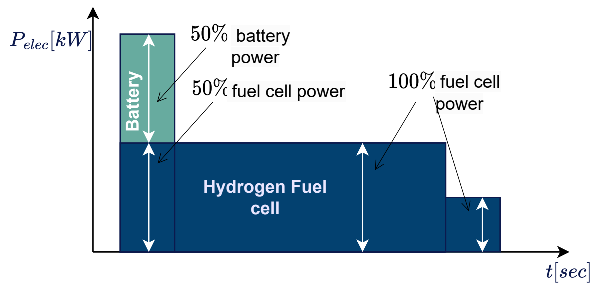

FIGURE 6. **Case-1: Schematic diagram of hybrid strategy for 100% fuel cell cruise mission**

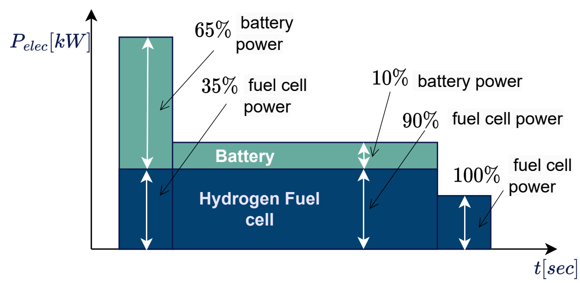

FIGURE 7. **Case-2: Schematic diagram of hybrid strategy for 90% fuel cell and 10% battery cruise mission**

VII. CASE STUDY

A. DESIGN STUDIES

In this paper, we consider the Dornier/RUAG Do 228NG, a regional aircraft, as the baseline for the HEA-H2B and investigate the potentially feasible sizes and critical parameters using our approach. Additionally, we consider two different design variants, Case-1 and Case-2, based on varying definitions of hybridization for the battery and hydrogen fuel cells. The definitions of hybridization for the design studies are outlined in Table 3. Fig. 6 illustrates the design for Case-1; during the cruise segment, the required electrical power is solely sourced from the fuel cell. However, maximum continuous power is drawn from the fuel cell during high-power mission segments such as climbing and takeoff, with supplementary power from the battery. Fig. 7 shows the design for Case-2, indicating that 10% of the electrical power required during the cruise segment is sourced from the battery, while 90% is provided by the hydrogen fuel cell. During other mission phases, a combination of power from the hydrogen fuel cell and the battery is used. It is important to note that Fig. 6 and Fig. 7 serve only as illustrations. The case study's hybridization strategy for takeoff, climbing, and other segments may vary depending on the scenario.

B. DESIGN REQUIREMENTS

A commuter-class aircraft category, such as the 19-seat CS-23 commuter aircraft, requires a maximum takeoff mass of up to 8618 kg and a payload of 1960 kg. These design requirements and mission specifications are detailed in Table 6. Additionally, the mission requirements and the definitions for each

TABLE 1. Validation of the analysis method for battery energy system

Names	methodA	methodB	Proposed	A's%Δ	B's%Δ
m_{TO},[kg]	8170	8290	8655.64	+5.944	+4.559
P/W,[W/N]	18.65	18.63	18.19	-2.466	-2.361
W/S,[N/m^2]	1957	1958	1968.51	+0.596	+0.545
m_{motor},[kg]	270	270	261.81	-3.355	-3.355
m_{strut},[kg]	4515.09	4421.27	4717.32	+6.696	+4.478
m_{batt},[kg]	1535.17	1505.02	1600.04	+6.313	+4.225

TABLE 2. Validation of the analysis method for hydrogen fuel cell energy system

Names	[26]	Proposed	% Δ
m_{TO}, [kg]	10113.1	10371.8	+2.558
P/W, [Watt/N]	18.33	18.19	-0.763
W/S, [N/m^2]	1953.1	1968.68	+0.797
m_{struct}, [kg]	4515.09	4563.59	+1.071
m_{FC}, [kg]	1332.4	1219.45	-8.477
m_{tank}, [kg]	1977.67	2112.54	+6.819

TABLE 3. Definitions of hybridization for the design study

Name	HP_{cruise}	$HP_{\text{takeoff}}, HP_{\text{climb}}, HP_{\text{loiter}}, HP_{\text{descent}}$
Case-1	$H_P = 0$	$0 \le H_P \le 1$
Case-2	$H_P = 0.1$	$0 \le H_P \le 1$

segment are explained in Fig. 8, which depicts information for each segment regarding speed, distance, and time. The main and reserve mission profiles are also considered for comprehensive mission coverage.

C. MODELING OF UNCERTAIN PARAMETERS

The fuzzy function is modeled as explained in Section IV-A1 for aerodynamics, mass fraction, and electric propulsion technology uncertainty. The historical data results based on several samples are shown in Table. 4, and statistical descriptors such as the mean, upper limit, and lower limit are derived from histograms. An example of the structural mass fraction is illustrated in Fig. 9. The electric propulsion technology uncertainty parameters are modeled using a confidence interval (CI), which is employed to establish the lower and upper limits of the fuzzy interval. However, addressing the battery-specific energy density presents a unique challenge, as only pack-level data is available. To tackle this limitation, a packing factor of 25% [27] is applied to correct cell-level data when estimating pack-level energy density. An example of confidence interval regressions is presented in Fig. 10 for battery energy density according to EIS year. Throughout this study, a forecast horizon of 2035 is assumed for the future development of the aircraft. The regression models and confidence intervals for the electrical system parameters are shown in Table. 5.

D. FORMULATION OF THE POSSIBILITY-BASED DESIGN OPTIMIZATION

The optimization task involves deterministic design variables (d) and uncertain parameters (p), while this study does not consider uncertain design variables (x). A detailed list of the constraints, the objective function (f), and deterministic design variables (d) is shown in Table. 6. Twenty-three uncertain parameters with upper limits, lower limits, and mean values are derived from historical data in Table. 4 and regression models with a 95% confidence interval from Table. 5. The design constraints are derived from reference [25] and CS 23 requirements.

VIII. RESULTS AND DISCUSSION

A. POSSIBLE FEASIBLE SIZING RESULTS

The optimal outcomes based on the target possibility index (α_t) are detailed in Table 7 at the designated optimum design point (d^*) and the mean value ($\bar{p}$) of the uncertain parameters for Case-1 and Case-2. In the deterministic scenario ($\alpha_t = 1$), the optimal solution features the lowest maximum takeoff mass. Both designs share identical values for the design variables (P/W) and (W/S). Notably, (m_{TO}) for Case-1 is lower than for Case-2, owing to the hybrid nature of the mission. Meanwhile, the increase in the target possibility index influences the performance constraints, allowing for a margin of uncertainty in the design parameters.

The mass breakdown at MPP for our case study highlights the optimistic to conservative possible design scenarios for two distinct aircraft, as illustrated in Fig.11 and Fig.12. This analysis elucidates how variations in the uncertain parameters influence the intended aircraft design. As α_t increases, we observe a corresponding rise in the maximum takeoff mass due to the worst possible combination of the uncertain parameters. Our findings demonstrate that to meet the CS.23 design requirements, a possibility index of 0.75 is attainable for the Case-2 design, while the Case-1 design can achieve an index of 0.7. Notably, the airframe mass makes the highest contribution to the total mass, while the hydrogen fuel mass and tank mass contribute comparatively less, owing to the high energy content of hydrogen. However, for Case-1, the battery mass decreases as (α_t) increases, while the mass of the fuel cell increases. This suggests that the maximum power of the hydrogen fuel cell can suffice to cover the entire mission, owing to the increased mass of the fuel cell system. In Case-2, both the battery mass and the mass of the fuel cell increase due to the high energy consumption during the cruising segment.

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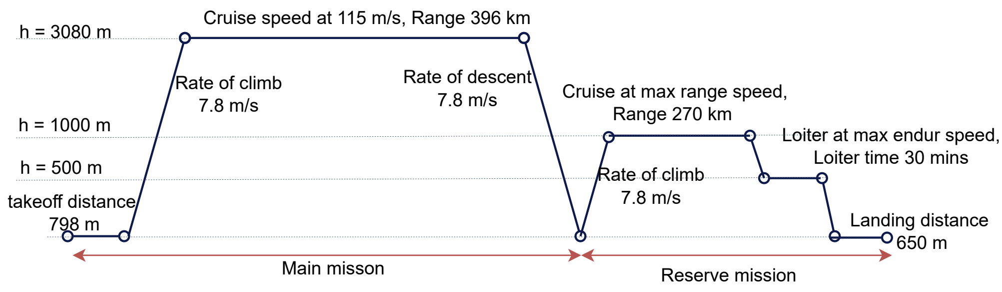

FIGURE 8. Mission profile for case study

TABLE 4. Aerodynamics, airframe and Tank GI historical data for fuzzy function

Parameters	lower limit	mean	upper limt	samples	references
C_{D_0}	0.02	0.0285	0.04	14	[22], [28]
e	0.628	0.76625	0.8	8	[22], [28]
$C_{L_{\max_{\text{clean}}}}$	1.26	1.8135	2.	14	[22], [29], [30]
$\Delta C_{D_{0_{TO}}}$	0.0058	0.0098	0.01	6	[21]
$\Delta C_{L_{flap}}$	0.3	0.4833	0.7	6	[21]
MF_{struct}	0.237	0.3007	0.405	10	[31]
MF_{avi}	0.002	0.0041	0.0.006	10	[31]
MF_{subsys}	0.051	0.1415	0.2251	10	[31]
$\eta_{\text{prop}_{\text{cruise}}}$	0.6	0.85	0.9	2	
$\eta_{\text{prop}_{\text{climb}}}$	0.6	0.675	0.9	2	[22]
$\eta_{\text{prop}_{\text{TO}}}$	0.35	0.5125	0.65	8	[22]
f_{install}	1.05	1.175	1.3	$\sim$	[24]
DoD	0.8	0.825	0.85	$\sim$	[25]
GI	0.2	0.51828	0.95	35	[8], [12], [13], [32]

TABLE 5. Regression model according to EIS years of electric propulsion system

Regression model	95% CI at 2035 (lb, ub)	R^2	references
$P^*_{motor} = 0.513\mathbf{x} - 1029.608$	(9.03, 20.67)	0.332	[8], [9], [14], [10], [33]–[35]
$P^*_{MCU} = 1.216\mathbf{x} - 2445.056$	(11.439, 47.915)	0.227	[8], [9], [10], [33]–[35]
$P^*_{FC} = 0.0434\mathbf{x} - 86.311$	(0.572, 3.470)	0.062	[7]–[9], [34], [36]–[38]
$P^*_{batt} = -0.017\mathbf{x} + 26.0095$	(0.378, 3.774)	0.377	[6], [33], [37], [39]–[41]
$E^*_{batt} = 14.45\mathbf{x} - 29084.53$	(396.135, 613.815)	0.394	[6], [12], [33], [35], [37], [39]–[43]
$\eta_{motor} = 0.0009\mathbf{x} - 0.867$	(0.863, 0.992)	0.351	[8]–[10], [14], [33]–[35]
$\eta_{MCU} = 0.0086\mathbf{x} - 0.787$	(0.969, 0.988)	0.392	[8]–[10], [33]–[35]
$\eta_{FC} = 0.0004\mathbf{x} - 0.139$	(0.512, 0.876)	0.004	[7]–[9], [34], [36]–[38]
$\eta_{batt} = 0.0002\mathbf{x} + 0.375$	(0.863, 0.992)	0.001	[6], [12], [33], [35], [37], [39]–[43]

TABLE 6. PBDO formulation for hybrid-electric aircraft

Minimize:	$f : m_{TO}$		
Subject to:			
$g_1 : V_{\text{stall}}$	$\leq$ 34.5 m/s	Do228NG	
$g_2 : V_{\max}$	$\geq$ 115 m/s	Do228NG	
$g_3 : ROC_{\max}$	$\geq$ 7.9756 m/s	Do228NG	
$g_4 : G_{\text{OEI}}$	$\geq$ 0.7%	CS23.65	
$g_5 : S_{\text{TO}}$	$\leq$ 793 m	CS23.59	
$g_6 : m_{\text{TO}}$	$\leq$ 8618 kg	CS23.2005	
Design variables:	d_0	lb	ub
$d_1 : P/W$	30	8	40
$d_2 : W/S$	1600	600	2500

TABLE 7. PBDO optimum at $(\boldsymbol{d}^*, p_i)$ for different possibility indices

Name	$\alpha_t = 1$	$\alpha_t = 0.9$	$\alpha_t = 0.8$	$\alpha_t = 0.75$
P/W, [W/N]	19.94	21.80	24.33	25.60
W/S, [N/m^2]	1674.58	1622.29	1558.38	1529.33
V_{stall}, [m/s]	34.5	33.95	33.28	32.96
$V_{\max}$, [m/s]	115	117.5	120.73	122.17
$ROC_{\max}$, [m/s]	9.70	10.94	12.63	13.47
G_{OEI}, []	0.066	0.081	0.10	0.11
S_{TO}, [m]	410.78	389.22	365.65	355.87
Case-1: m_{TO}, [kg]	5082.08	5131.04	5198.90	5233.09
Case-2: m_{TO}, [kg]	5572.17	5665.42	5771.58	5830.25

This analysis indicates that hybrid-electric aircraft designed to meet the CS23 requirements, with a maximum

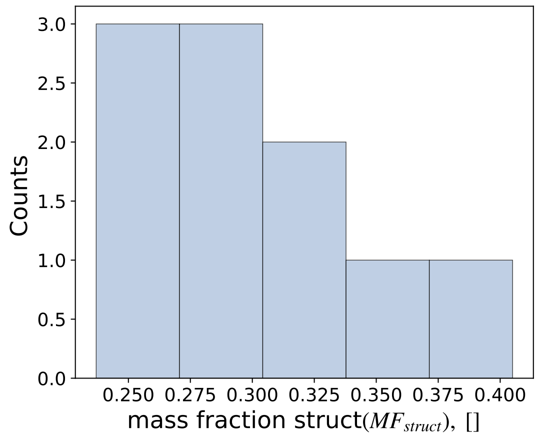

FIGURE 9. **Example of historigam of fuzzy function for structural mass fraction**

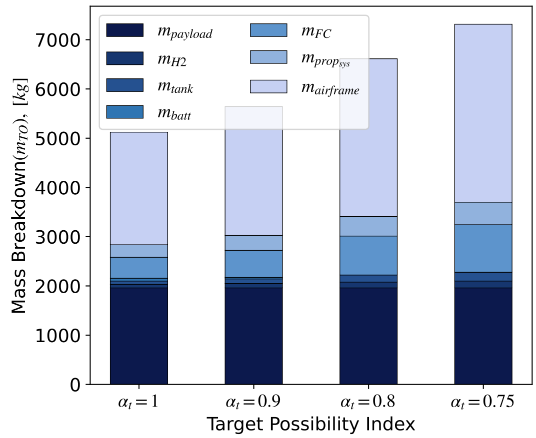

FIGURE 11. **Mass breakdown at (d^*, p_{mpp}) and for different possibility index (α_t) for Case-1**

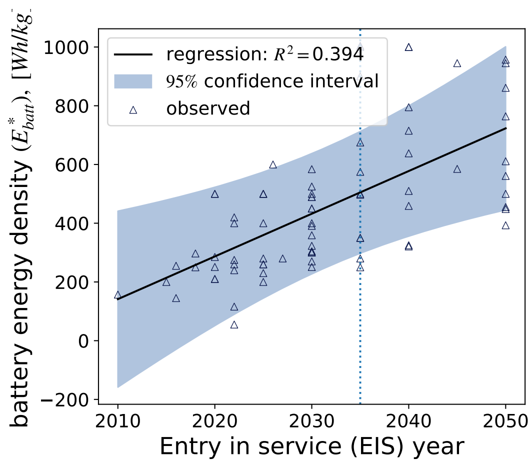

FIGURE 10. **Example of confidence interval regression of fuzzy function for battery energy density**

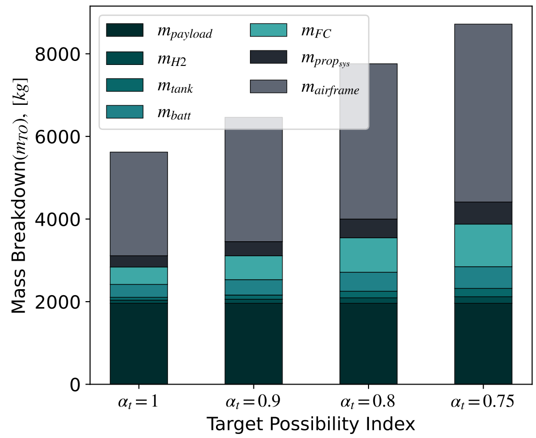

FIGURE 12. **Mass breakdown at (d^*, p_{mpp}) and for different possibility index (α_t) for Case-2**

payload of 1960 kg, can still be feasible to develop. This underscores the possible sizing results across the possibility indices, accounting for technology and analysis uncertainty at the early design stage.

B. ASSESSMENT OF ACTIVE CONSTRAINTS AND CRITICAL PARAMETERS

The critical parameters constraining the feasible sizes of the HEA-H2B are those affected by the design constraints or requirements. Constraints at the optimum design point (d^*) are depicted in Fig. 13, showing the possible feasible sizing results and limiting constraints. Stall speed and maximum speed constraints exhibit activity for possibility index values of 1, 0.9, 0.8, and 0.75, while other constraints remain inactive. This observation suggests that, for the development of aircraft similar to the HEA-H2B, the stall speed and maximum speed constraints are more significant than constraints such as the takeoff distance, maximum rate of climb, and climb gradient. Moreover, the maximum takeoff mass constraint becomes active when the index approaches 0.7 for Case-2 and 0.75 for Case-1. Beyond a possibility index of 0.7, the PBDO optimizer fails to identify an optimum solution without violating the design constraints regarding maximum takeoff mass, indicating an infeasible design space.

The most significant uncertain parameters at the MPP are also illustrated in Fig. 14, focusing on the maximum takeoff mass constraint across various values of (α_t), represented using a triangular fuzzy membership function. It is evident that nearly all parameters exhibit activity concerning the maximum takeoff mass, while (P^*_{batt}) is solely active for Case-1. In contrast, parameters such as (E^*_{batt}), (DoD), and (η_{batt}) are active for Case-2. This provides valuable insights for the further design stage of hybrid electric aircraft, indicating that designs using batteries for high-power mission segments need to focus primarily on investigating (P^*_{batt}) rather than energy density. However, designs employing battery energy during cruise phases should prioritize the examination of (E^*_{batt}), (DoD), and (η_{batt}) over (P^*_{batt}).

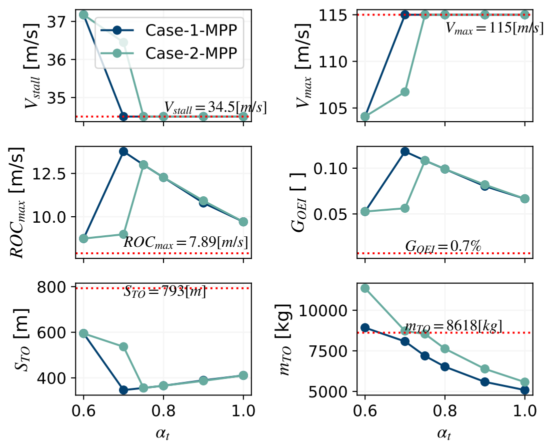

FIGURE 13. **The constraints value at most probable points for different possibility index at optimum design**

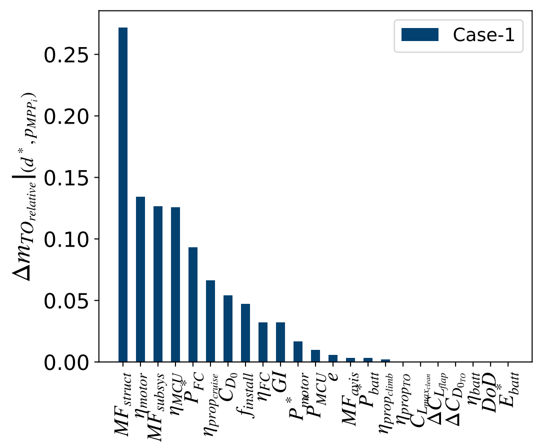

FIGURE 15. **Relative change of maximum takeoff mass due to 10% variation in due to active uncertain parameters at (α_t) of 0.75 for Case-1**

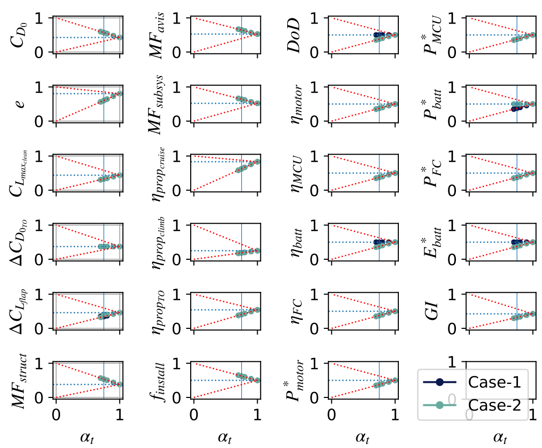

FIGURE 14. **Normalized active MPP uncertainty parameters on a fuzzy function for maximum takeoff mass constraints of Case-1 and Case-2 design studies**

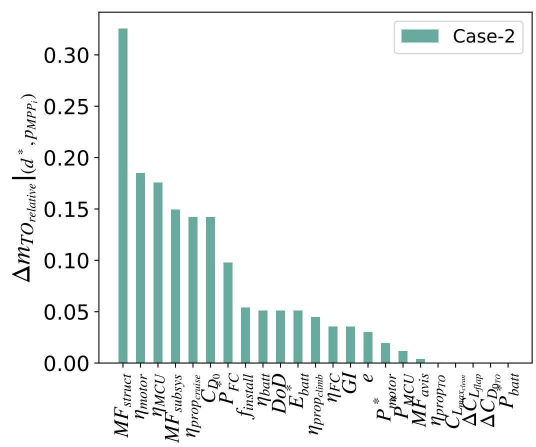

FIGURE 16. **Relative change of maximum takeoff mass due to 10% variation in due to active uncertain parameters at (α_t) of 0.75 for Case-2**

C. SENSITIVITY ANALYSIS OF MPP PARAMETER

A sensitivity analysis is conducted at the MPP of each constraint to assess the significance of every uncertain parameter relative to each design constraint to be addressed in the mature design stage, targeting a possibility index of 0.75, where both the designs for Case-1 and Case-2 are feasible, as shown in Fig.13. The analysis for design constraints such as stall speed, cruise speed, maximum climb rate, OEI climb gradient, and takeoff distance is provided in AppendixA, as the results align with those of traditional sensitivity analysis. However, for the maximum takeoff mass constraint, the analysis results are shown in Fig.15 for Case-1 and Fig.16 for Case-2, and the discussion is provided.

Aerodynamic configuration parameters, which are directly affected by aircraft configurations, including (C_{D_0}, e, and η_{prop}), hold critical significance for both aircraft designs. However, the (C_{D_0} and η_{prop}) in the design for Case-2 exert a more dominant influence compared to those in the design for Case-1, because most of the energy (E^*_{batt}) is used in cruise segments, which increases the battery weight, resulting in a high variation in maximum takeoff mass.

The parameters related to airframe technology, (MF_{struct} and MF_{subsys}) of the aircraft structure, have the most substantial impact, with relative changes of around 0.3 for both cases. This underscores the criticality of aircraft structures, encompassing materials and structural properties, among the uncertain design parameters for both designs. Regarding the parameters of the electric propulsion technology, ranging from (η_{motor}) to (η_{MCU}, $\eta_{\text{propcruise}}$, f_{install}, η_{FC}, P^*_{motor}, and P^*_{MCU}), their importance varies from around 0.15 to 0.1 for Case-1 and from 0.2 to 0.15 for Case-2.

Energy system parameters, such as the power density of (P^*_{FC}, η_{FC}, and GI), play critical roles in both designs due to their reliance on hydrogen fuel cells for energy. However, (P^*_{batt}) is significant only for the design using batteries for high-power mission segments, such as the design in Case-1. Parameters like (η_{batt}, DoD, and E^*_{batt}) are equally crucial for the design employing battery energy during cruise phases. It is noteworthy that battery energy density does not universally dictate the performance of the hybrid electric aircraft. Only (P^*_{batt}) is dominant when the battery serves solely as an auxiliary power system. However, if the battery powers high-energy consumption segments, like the cruise phase, parameters such as (E^*_{batt}, η_{batt}, and DoD) become paramount.

In summary, while uncertain parameters impact performance constraints like stall speed, maximum speed, rate of climb, OEI climb gradient, and takeoff distance in similar ways for both case studies, the constraint of maximum takeoff mass stands out, especially in hybridization missions, as shown in Fig. 6 and Fig. 7. Notably, the efficiencies of the electric systems, including (η_{motor}, η_{MCU}, and η_{prop}), have a stronger influence on maximum takeoff mass than the power density specification (P^*) of electric propulsion systems. This highlights the importance of high-efficiency electric propulsion systems, emphasizing power output efficiency over mere mass reduction. Interestingly, the installation effect (f_{install}) shows more variability compared to energy system factors such as (GI, P^*_{batt}, and E^*_{batt}) under a 10% variation in the uncertain parameters. The installation effect directly affects the total propulsion system, influenced by factors like the number of motors and propellers, while energy system variables primarily impact mission analysis, particularly in hybridization scenarios.

This underscores that different investigations are warranted in the mature design of hybrid electric aircraft like the HEA-H2B, such as the Case-1 and Case-2 designs. For instance, Case-1, relying mainly on battery power during high-power segments, should prioritize scrutiny of (P^*_{batt}), whereas Case-2, using battery energy during cruise segments, should focus on (η_{batt}, DoD, and E^*_{batt}) rather than the power density (P^*_{batt}). Notably, (MF_{struct}) emerges as the most critical parameter for reducing the aircraft mass, followed by electric propulsion efficiencies and aerodynamic parameters.

Our approach demonstrates that using possibility-based design optimization coupled with a sizing method provides a thorough understanding of each design parameter. By ensuring coverage of bounds on the uncertain data through (α_t) and identifying active parameters at the MPP of failure, this method effectively addresses the potentially possible feasible sizing results by different possibility indices and critical parameters aspects necessary for the mature design stage in the development of hybrid-electric aircraft incorporating hydrogen fuel cells and battery technology.

D. LIMITATIONS OF OUR STUDY

This study presents an effective strategy for accounting for various sources of uncertainty in parameters to achieve feasible sizing outcomes in the early design stage of hybrid electric aircraft. Current research focuses on the sizing aspect of electric aircraft and considers system-level uncertainty parameters, which may limit detailed analyses of aerodynamics and propulsion factors. Therefore, the equations in sizing methods include epistemic uncertainty, which is modeled as a fuzzy function in our approach. In addition, the hybridization strategy in the case study missions is also limited to scenarios that need to be considered by fuel cell maximum continuous power. Additionally, a sensitivity analysis was conducted with only a 10% variation in parameters to highlight the importance of each parameter for the design constraints. It is recommended that the quantification of uncertain parameters for electric systems be thoroughly investigated at the conceptual design stage, with detailed analysis and evaluation of performance and mission outcomes.

IX. CONCLUSIONS

Sustainable aviation can be achieved by advancing aircraft propulsion systems through hybrid electric technology. However, the sizing methods for such aircraft involve several uncertainties, impacting development time and cost. We present a possibility-based sizing approach to address uncertainties in electric propulsion, airframe technology, and configuration parameters, significantly advancing electric aircraft development. We validated our sizing method, showing a 6.6% difference for battery-electric aircraft and an -8.48% difference for hydrogen fuel cell aircraft compared to existing literature.

By employing 23 uncertainty parameters as fuzzy membership functions within a PBDO optimization framework, we analyzed two hybrid electric aircraft variants targeting CS23 certification. Our findings indicate that stall and maximum speed are critical limiting factors, with feasible design regions diminishing as reliability increases. The maximum takeoff mass aligns with CS23 requirements at a possibility index of 0.75, primarily due to incorporating safety margins within hybrid energy systems. Sensitivity analysis revealed that airframe technology significantly impacts maximum takeoff mass, followed by electric propulsion efficiency and aerodynamic design. The propulsion system integration is particularly critical, with battery energy density varying by mission segment.

Overall, our framework serves as a valuable tool for early-stage aircraft design, assisting in meeting design requirements and identifying critical technologies essential for the subsequent design process of electric aircraft development.

APPENDIX A
SENSITIVITY ANALYSIS FOR CONSTRAINTS AT MPP

- *Stall speed (V_{stall}) and Maximum Speed (V_{max}):*
  The clean configuration $C_{L_{\text{max}_{\text{clean}}}}$ and $\Delta C_{L_{\text{flap}}}$ emerge as the most influential parameters for the stall speed constraint. The coefficients of C_{D_0} and η_{prop} exert a significant influence on the maximum speed of the aircraft. Oswald span efficiency e only has a minor impact on the maximum speed constraint. This highlights the critical importance of the lift coefficient of a clean configuration of the wing and the airfoil in designing low-speed aircraft aerodynamically efficient design and high-efficiency propellers in designing high-speed aircraft.

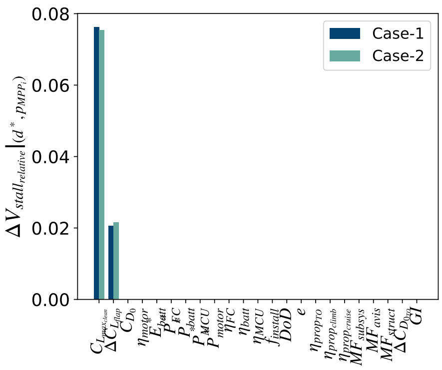

FIGURE 17. Relative change of stall speed due to 10% variation in due to active uncertain parameters at (α_t) of 0.75

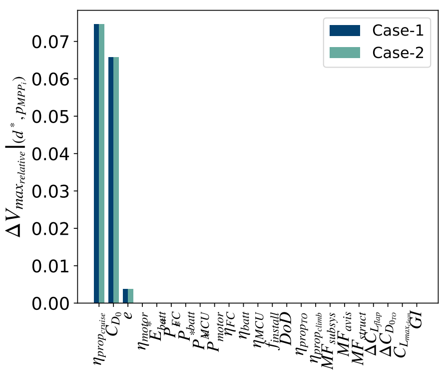

FIGURE 18. Relative change of cruise speed due to 10% variation in due to active uncertain parameters at (α_t) of 0.75

- *Maximum rate of climb (ROC_{max}) and OEI climb gradient (G_{OEI}):*
  The maximum rate of climb is also influenced by C_{D_0}, e, and η_{prop}. In the case of one engine inoperative (OEI) climb condition, e emerges as more dominant than the effect of C_{D_0}, highlighting the significance of span efficiency. Aircraft with high-span designs will exhibit greater efficiency compared to lower-drag designs, especially in redundant design scenarios. Moreover, it is noteworthy that high-efficiency propellers play the most critical role in determining the OEI climb gradient.
- *Takeoff distance (S_{TO}):*
  The takeoff distance constraint is primarily determined by several factors ranked from highest to lowest impact: $C_{L_{\text{max}_{\text{clean}}}}$, $\eta_{\text{prop}_{\text{TO}}}$, $\Delta C_{L_{\text{flap}}}$, C_{D_0}, e, $\Delta C_{D_{0_{TO}}}$. This indicates that a clean configuration with maximum lift coefficient, the use of high-lift devices or distributed propulsion during takeoff, and the adoption of high-efficiency propeller technologies are critical for designing short-takeoff and landing aircraft.

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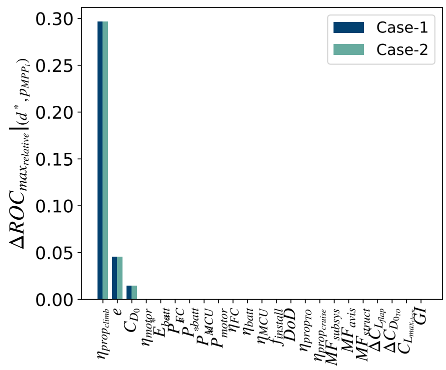

FIGURE 19. Relative change of climb rate due to 10% variation in due to active uncertain parameters at (α_t) of 0.75

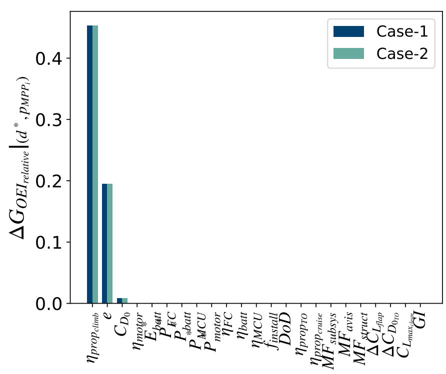

FIGURE 20. Relative change of OEI climb gradient due to 10% variation in due to active uncertain parameters at (α_t) of 0.75

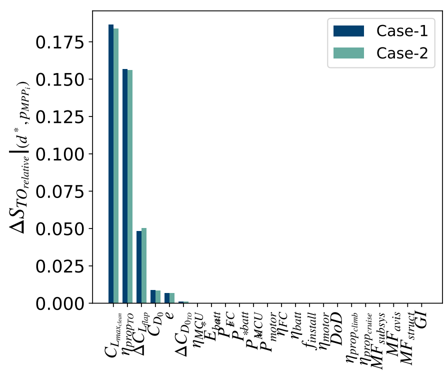

FIGURE 21. Relative change of takeoff distance due to 10% variation in due to active uncertain parameters at (α_t) of 0.75

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