Framework for Technical Performance Uncertainty in Hybrid-Electric Aircraft Development

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***Abstract*— When working at the cutting edge of technology development, it is essential to understand the state of the technical performance as project testing and modeling progresses to recognize how component changes may impact the end product. This is especially true for hybrid-electric aircraft, where the implementation and operations of the electric propulsion systems have an impactful effect on the overall system performance. This paper proposes a framework for uncertainty evaluation of a hybrid-electric vehicle through the project's lifespan. The framework uses Monte Carlo analysis with the vehicle's electrical component variables to find the uncertainty in key aircraft parameters such as mission range, fuel used, and electrical energy used during cruise. The framework is applied to a parallel hybrid De Havilland Canada Dash 8-400 aircraft. It is determined that battery specific energy and battery efficiency uncertainty has the largest influence on the key aircraft performance parameters.**

Keywords—hybrid electric aircraft, uncertainty

I. Introduction

Transportation sectors around the globe are working to improve efficiency to reduce emissions. The aviation sector alone produces 2.1% of all human-induced CO2 emissions and uses 7-8% of all global liquid fuel [1]. Demand for flights show no indication of slowing, with a 10.4% increase in revenue passenger kilometers in 2024 when compared to that from 2023 and 3.8% increase from pre-pandemic 2019 levels [2]. Simultaneously, airlines are looking for methods to reduce fuel usage for not only environmental concerns, but as a cost saving measure as well. Fuel is usually the largest cost for airlines, at 28.7% of total airline cost [3]. Hybrid-electric aircraft are a promising solution to both the environmental and industrial fuel cost concerns. Through the use of electrified aircraft propulsion (EAP) technologies, hybrid-electric aircraft can reduce carbon emissions and fuel use of aircraft, while still benefitting from the advantages of internal combustion engines [4]. Even greater positive environmental impacts can be achieved if the hybrid aircraft burns sustainable aviation fuel (SAF) [5]. NASA is developing EAP technologies and hybrid-electric aircraft through the Advanced Air Transport Technology (AATT) project [6].

Hybrid-electric aircraft projects operate on the cutting edge of technology development, and when working on state-of-the-art technology it is essential to understand the state of the technical performance as project testing and modeling progresses. This is especially true for hybrid-electric aircraft, where component changes or implementation and operations of the electric propulsion system have an impactful effect on the overall system performance. However, there is still a lot of uncertainty associated with the models being developed, as hybrid-electric aircraft technology is still in the early developmental stages. This paper proposes a framework for the uncertainty evaluation of a hybrid-electric vehicle through its project's lifespan, with a focus on the uncertainty from the electrical components of the aircraft.

A survey of the research done in this area includes that of Diamantidou et al. who modeled and performed uncertainty analysis on a 19 passenger aircraft with a series hybrid-electric propulsion system to compare two entry-into-service scenarios [7]. Milios et al. modeled a 150 passenger aircraft with parallel hybrid-electric propulsion [8], which was followed up with uncertainty quantification on different propulsion architectures through deterministic design optimization, design optimization under uncertainty, and uncertainty propagation on design optimization [4][9][10]. The methodology used in these prior works are built upon in this paper to focus on the uncertainty of a selected hybrid aircraft design with the goal of a flight test, rather than that of future aircraft or aircraft that are still in the design phase. The framework can be applied to most hybrid-electric aircraft designs, but for the purposes of this paper is applied to a parallel hybrid De Havilland Canada Dash 8-400 (Dash 8) aircraft with a PW150A engine. The initial modeling of this aircraft was done in Listgarten et al. [11], and the uncertainty methodology for this architecture is explored in this paper.

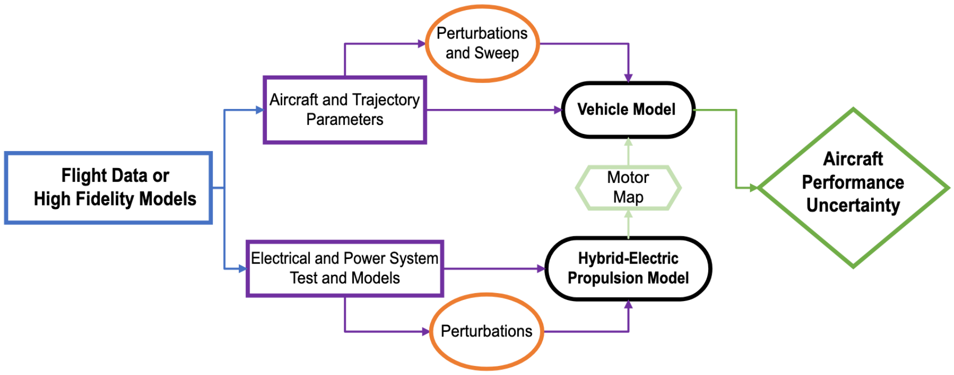

Fig. 1. Aircraft performance uncertainty framework

II. Methodology

The developed methodology is presented in Fig. 1. Flight test or high fidelity model data (blue rectangle) is collected throughout the duration of the project. Of that data, the aircraft and trajectory parameters and the electrical and power system data (purple rectangles) are fed into the vehicle synthesis and hybrid-electric propulsion modeling tools (black rounded rectangles). The propulsion model inputs are then perturbed (orange ellipses) given any testing or predicted uncertainty. The resulting associated efficiencies at specified torques and shaft speeds are fed into the vehicle analysis tool as a motor map. The aircraft or flight parameters going into the vehicle model are perturbed or swept as well, depending on the uncertainties measured and aircraft performance variables desired. The output of the vehicle model is finally formulated into potential ranges of mission parameters (green diamond). The model performance is compared against lab and ground test data. As testing progresses the models are updated and recalibrated, and the level of uncertainty in the aircraft performance is reassessed.

III. Modeling Tools

This section covers the vehicle model and power electronics architectures utilized in the framework proposed. Further details can be found in the work done by Listgarten et al. [11], but a brief overview of the relevant information is provided.

A. *Numerical Propulsion System Simulation (NPSS)*

NPSS is an engine simulation tool that allows for design and analysis of propulsion systems [12]. Recent development of the Electrical Port in NPSS enables the modeling of hybrid-electric propulsions systems [13]. The NPSS Power System Library (PSL) utilizes both physics-based equations and maps to characterize the efficiency of a given electrical component.

B. *General Aviation Synthesis Program on Condor (Gascon)*

Gascon [14] is a python NASA in-house vehicle synthesis tool developed using the Condor framework [16]. It is created to be a modern alternative to the 1970s Fortran tool General Aviation Synthesis Program (GASP). Gascon performs tasks associated with early-stage aircraft design such as vehicle sizing, allowing for rapid parametric studies during the conceptual design phase [11]. It retains the capabilities of GASP while allowing for future development of novel aircraft.

IV. Vehicle Model and Mission

For this study, a De Havilland Canada Dash 8-400 (Dash 8) aircraft with two PW150A engines has been chosen as the aircraft model to hybridized and apply uncertainty to. The baseline model was made using publicly available data, and the assumptions made to the hybridized model are listed in Table I. Parallel hybridization is implemented, where the free turbine is connected to a combination reduction/combining gearbox with the motor and the internal spools of the turboprop engine are untouched. The combined gearbox allows the motor and turbine to power the propeller together. A schematic of the parallel hybrid propulsion architecture is shown in Fig. 2. Further information about the model is described in Listgarten et al. [11].

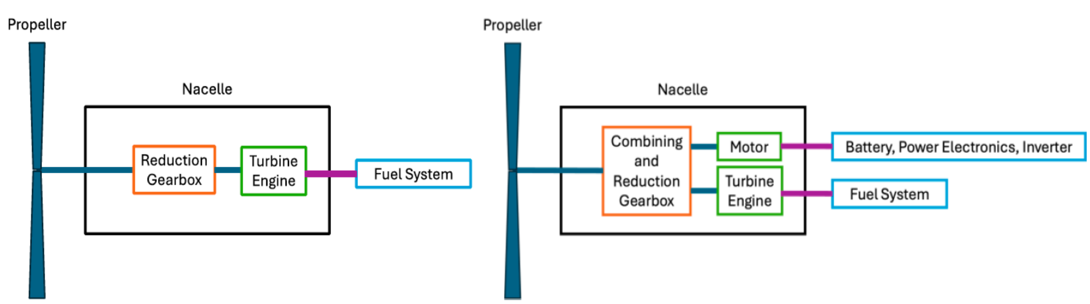

Fig. 2. Conventional turboprop (left) and parallel hybrid turboprop (right)

The mission the Dash 8 model will fly is shown in Fig. 3. The aircraft will taxi and climb conventionally. Part way through the climb, the electric motor will turn on and assist the engine in generating thrust. The altitude at which the electric motor turns on is called "motor-on altitude" in this paper. When the cruise altitude is reached, the thrust is split according to the motor–engine thrust split parameter, subsequently called the "thrust split" in this paper. After cruising for as long as possible, the aircraft will descend and attempt a conventional reserve mission.

Perturbations in the hybrid-electric propulsion system are made and fed into Gascon using a Monte Carlo method. The parameters chosen for perturbation are shown in Table II. Electrical component efficiencies, specific powers, and specific energies would bring in uncertainties that can be tracked and improved upon with testing. These parameters would normally be assessed and determined through testing, but for the purposes of this paper the variable ranges are from literature and are spread into a triangular distribution [4]. Mission specific parameters include the thrust split, motor-on altitude, and cruise altitude. These parameters are varied during the analysis to provide insight on the capabilities and uncertainties of the vehicle's performance.

TABLE I. DASH-8 MODEL PARAMETERS AND VALUES

Aircraft Parameter	Gascon Model Value
Takeoff Weight	63,750 lb
Operating Empty Weight	38,168 lb
Payload Weight	62 pax, 200lbs each
Motor Size	950 kW
Cruise Mach	0.4125
Cruise Altitude	25,000 ft

TABLE II. DASH-8 MODEL AND MISSION VARIABLES

Parameter	Default Value	Min Value	Max value
Inverter Specific Power, kW/kg	13.8	9.6	17.3
Inverter Efficiency, %	0.985	0.982	0.988
Battery Specific Energy, kWh/kg	0.489	0.359	0.584
Battery Efficiency, %	85	80	90
Motor Specific Power, kW/kg	13.2	9.2	16.1
Thrust Split, %	20% -80%, at 20% increments		
Motor-on Altitude, ft	10,000 ft to 25,000ft , at 5,000 ft increments[a]		
Cruise Altitude, ft	15,000 to 30,000 ft, at 5,000 ft increments		

[a] Always kept below cruise altitude

V. RESULTS

A. Aircraft Performance Parameters

The range and fuel burned of the Dash 8 aircraft cruising at 25,000 ft as the motor-on altitude changes are shown in Fig. 4 and 5. The thrust splits range from 20% to 80%. The shaded regions represent the minimum and maximum values that can be expected from the electrical component uncertainties. Both fuel burned and mission range show the same trends because they are directly influenced by the other. The aircraft has a smaller range with a higher thrust split due to the smaller energy density of the battery compared to that of jet fuel.

The median values and uncertainty range for the 20% and 80% thrust split cases of range and fuel burned are shown in Table III. As the motor provides more torque to assist the engine, there is a significant drop in range and fuel burned. The median aircraft range drops around 70% between the 20% and 80% thrust splits. However, the uncertainty remains relatively unchanged at around +23% to -25%. Both the fuel burn value and uncertainty drop when thrust split increases from 20% to 80%, with the median fuel burn value dropping around 50% and the fuel burn uncertainty ranging 11% to -14% to ranging 5% to -5%. A tighter uncertainty bound is more desirable for a project since it provides a better prediction of the end aircraft performance.

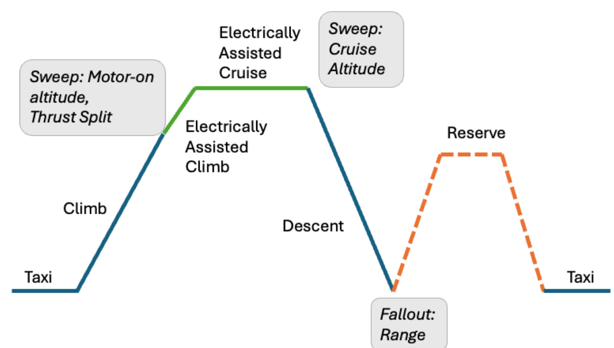

Fig. 3. Vehicle Mission

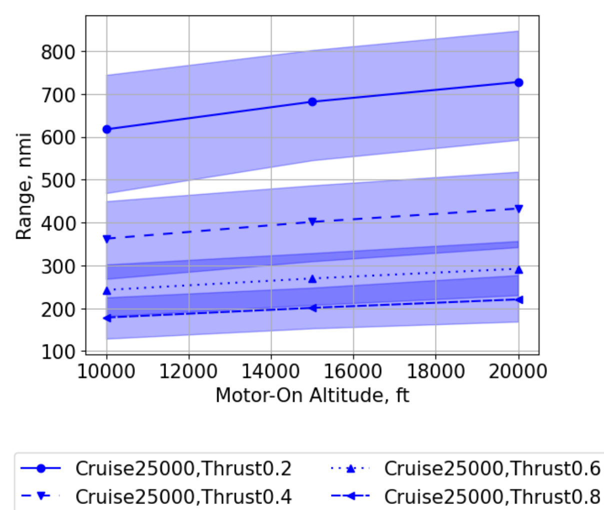

Fig. 4. Mission range v. motor-on altitude for hybrid-electric Dash 8 cruising at 25,000 ft. Shaded area represent uncertainty regions

The range of the aircraft v. the motor-on altitude for thrust splits of 20% and 80% is shown in Fig. 6. The cruise altitude is swept from 15,000 to 30,000 ft. As the cruise altitude increases, the range values between the two thrust splits become more similar. This follows the logic of less battery energy being available after climb to vary the overall range during cruise.

Median and uncertainty ranges of Fig. 6 are shown in Table IV. At higher altitudes, the uncertainty of the aircraft range remains relatively unchanged with a change in thrust split. At a 30,000 ft cruise, the average lower bound between 20% and 80% thrust splits remains at -22% while the average upper bound increases from 16% to 22%. The uncertainty greatly increases at lower altitudes. At a 15,000 ft cruise, there is a 10 to 17% change in uncertainty bounds.

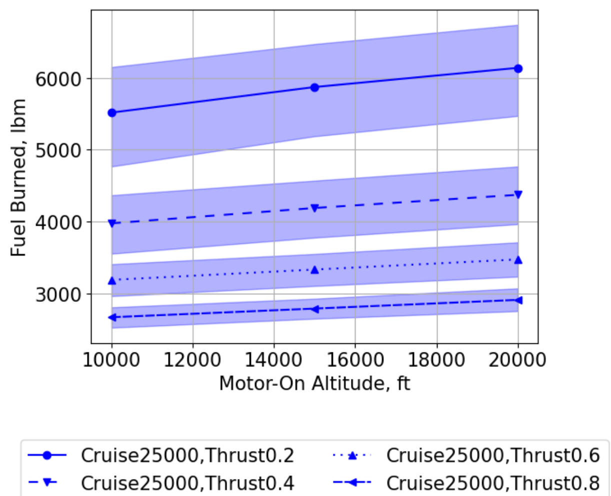

Fig. 5. Fuel burned v. motor-on altitude for hybrid-electric Dash 8 cruising at 25,000 ft. Shaded area represent uncertainty regions

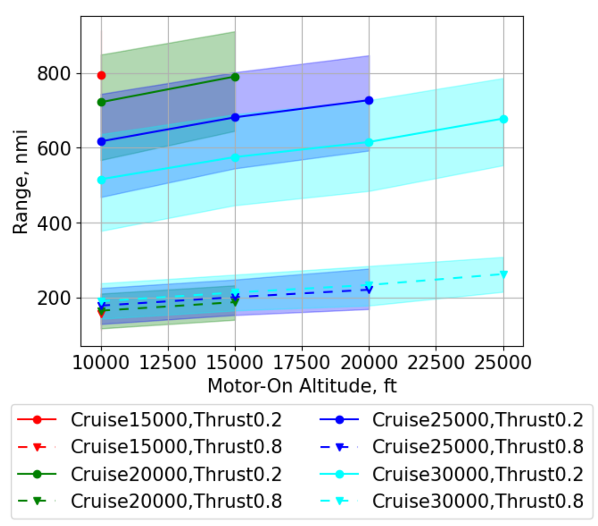

Fig. 6. Range v. motor-on altitude for hybrid-electric Dash 8 for thrust splits 20% and 80%. Shaded area represent uncertainty regions

The electrical energy used during cruise v. cruise altitude for a thrust split of 20 and 80% is shown in Fig. 7. The altitude at which the motor is turned on is swept from 10,000 ft to the run's cruise altitude. As the motor-on altitude increases or the cruise altitude decreases, there is more electrical energy left for cruise.

Table V shows the cruise electrical energy uncertainty values for cruise altitude of 15,000 ft and 30,000 ft and thrust splits for 20% and 80%. Across the board, increasing thrust split or decreasing the time in cruise by increasing cruise altitude or lowering the motor-on altitude increase the uncertainty in the electrical energy used during cruise.

TABLE III. UNCERTINATY BOUNDS FOR RANGE AND FUEL BURNED OF HYBRID-ELECTRIC DASH 8 CRUISING AT 25,000 FT

	Range		Fuel burned	
	Thrust split 20%	Thrust split 80%	Thrust split 20%	Thrust split 80%
Average lower bound	-25%	-25%	-14%	-5%
Average upper bound	20%	25%	11%	5%
Median value	620-730 nmi	178-220 nmi	5520-6140 lbm	2670-2910 lbm

TABLE IV. UNCERTINATY BOUNDS FOR RANGE OF HYBRID-ELECTRIC DASH 8 CRUISING AT 15,000 AND 30,000 FT

	Range			
	Cruise Alt 15,000		Cruise Alt30,000	
	Thrust split 20%	Thrust split 80%	Thrust split 20%	Thrust split 80%
Average lower bound	-19%	-29%	-22%	-22%
Average upper bound	15%	32%	16%	22%
Median Value	794 nmi	156 nmi	516-678 nmi	190-262 nmi

TABLE V. UNCERTINATY BOUNDS FOR CRUISE ELECTRIC ENERGY OF HYBRID-ELECTRIC DASH 8 CRUISING AT 15,000 AND 30,000 FT AND MOTOR-ON AT 10,000 AND 25,000 FT

		Cruise electrical energy, kWh			
		Motor-on alt 10,000 ft		Motor-on alt 25,000 ft	
		Thrust split 20%	Thrust split 80%	Thrust split 20%	Thrust split 80%
Cruise alt 15,000ft	Lower bound	-20%	-46%	-	-
	Upper bound	16%	51%	-	-
Cruise alt 30,000ft	Lower bound	-37%	-98%	-24%	-52%
	Upper bound	31%	100%	20%	50%

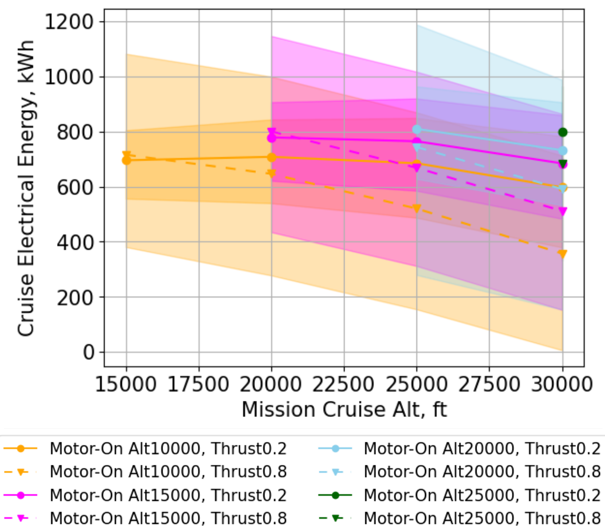

Fig. 7. Electrical energy used in cruise v. motor-on altitude for hybrid-electric Dash 8 for thrust splits 20% and 80%. Shaded area represent uncertainty regions

B. *Input Variables and r2 Values*

The r^2 value, or the coefficient of determination, is a statistical measure often used to estimate the "goodness of fit" of a linear regression. The r^2 value provides a simple description of the relationship between observed and predicted values [16] and is computed with (1). SSR is the sum of the residuals between the data and predicted values squared, and SST is the sum of the distances between the data and mean value squared. r^2 values are a percentage between 0 and 1, with 1 indicating a strong goodness of fit. For this paper, r^2 values are used to describe the relationship between the electrical component parameters and key aircraft performance parameters.

$$r^2 = 1 - ({}^{SSR}/_{SST}) \tag{1}$$

The r^2 values and perturbation ranges of the electrical component parameters varied in the model are listed in Table VI. For all output parameters, it is clear that battery specific energy is by far the most influential input with an r^2 value of 0.94, followed by the battery efficiency with an r^2 value of 0.12. Both the motor and inverter specific power variables have large distributions (around -30% to +25%) when compared to those from battery specific energy and efficiency (-19% to +27% and -6% to +6%), but barely influence the aircraft performance parameter results with negligible r^2 values.

When the battery specific energy is limited to -5% to +5% the median value, the uncertainty ranges drop significantly. Fig. 8, 9, and 10 show Fig. 4, 6, and 7 with the battery specific energy values limited.

TABLE VI. R^2 VALUES AND DISTRIBUTIONS OF ELECTRICAL COMPONENT PARAMETERS

	Variable dist. range	Aircraft performance parameters		
		Aircraft range	Fuel burned	Cruise electrical energy
Inverter specific power	-30%/ +25%	6.00E-05	6.00E-05	7.00E-05
Inverter efficiency	-0.3%/ +0.3%	1.00E-03	1.00E-03	6.00E-04
Battery specific energy	-27%/ +19%	0.94	0.94	0.94
Battery efficiency	-6%/ +6%	0.12	0.12	0.12
Motor specific power	-31%/ +22%	8.00E-03	8.00E-03	8.00E-03

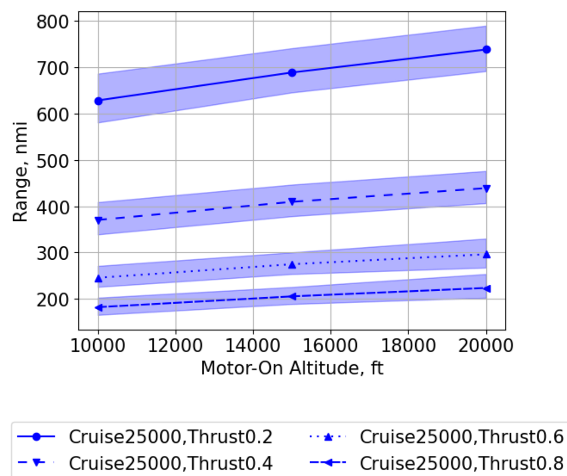

Fig. 8. Mission range v. motor-on when cruising at 25,000 ft. Battery specific energy distribution limited to ±5%

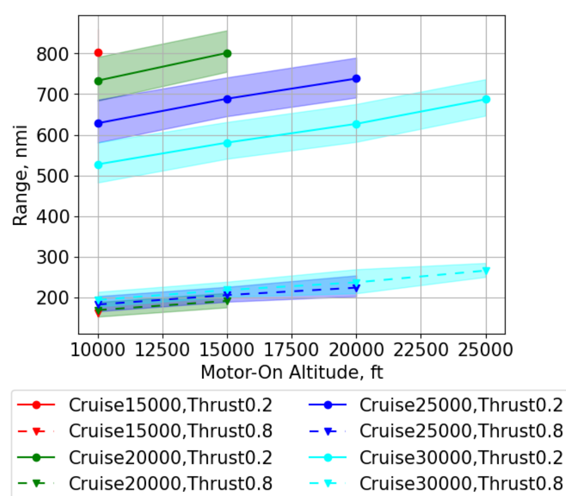

Fig. 9. Range v. motor-on altitude for thrust splits 20% and 80%. Battery specific energy distribution limited to ±5%

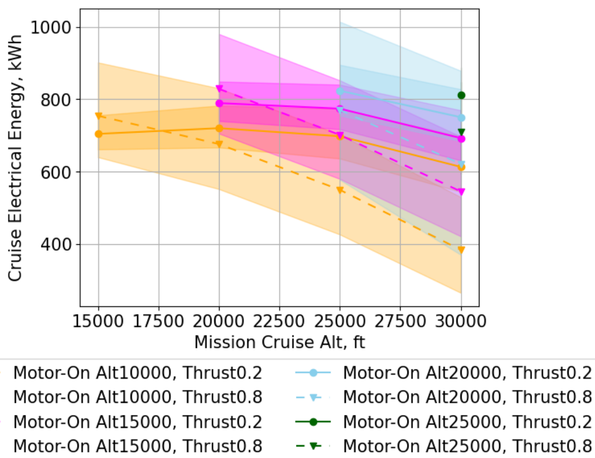

Fig. 10. Cruise electrical energy v. motor-on altitude for for thrust splits 20% and 80%. Battery specific energy distribution limited to ±5%

VI. Conclusions

This paper proposed a framework for uncertainty evaluation of a hybrid-electric vehicle through its project lifespan. The framework was applied to a parallel hybrid De Havilland Canada Dash 8-400 aircraft with a PW150A engine, with the context of understanding the performance parameters for a selected aircraft design. Monte Carlo analysis was performed on the model, focusing on the uncertainty from only the electrical components of the aircraft on the performance parameters. The uncertainty distribution of the electrical components would normally be found through component testing or high fidelity models, but triangle distributions from literature were used for the purposes of this paper.

The uncertainty on the aircraft mission range, fuel burned, and cruise electrical energy used were modeled. For a cruise altitude of 25,000 ft, it was determined that the range uncertainty remains relatively unchanged compared to the fuel burn uncertainty. Lower cruise altitudes, increasing thrust split, or decreasing the time in cruise also create larger uncertainty bounds.

Knowledge of the performance parameter uncertainty provides valuable information for project progress assessments. The mission cruise, motor-on altitude, and thrust splits all differently impact the uncertainty bounds, showing how parameter uncertainties may be influenced without directly changing any electrical components.

The r^2 values of the electrical component variables reveal how battery specific energy and efficiency uncertainty has the largest influence in aircraft performance parameters. Despite the larger distributions of the inverter and motor specific powers, they have negligible influence to the performance when compared to that from battery efficiency and specific energy. Thus, efforts to decrease battery specific energy and efficiency uncertainty is the most effective in decreasing parallel hybrid-electric aircraft performance uncertainty.

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