



Model-based fully coupled propulsion-aerodynamics optimization for hybrid electric aircraft energy management strategy



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ABSTRACT

Hybrid electric aircraft concepts are high in future aviation agenda to enabling reduced fuel consumption and emissions. However, the additional weight of the introduced battery and electrical components and sizing cascading effects will impact aircraft mission analysis performance. Therefore, the potential benefit of adopting hybrid electric aircraft will highly depend on the applied energy management strategy (EMS). This paper presents a three-layer propulsion-mission analysis-EMS integrated multi-objective optimization scheme for hybrid electric aircraft identifying feasible design aspects considering fully coupled propulsion-aerodynamics effects. The 'propulsion' layer comprises the propulsion system modelling, integration approaches, and performance synthesis using an Artificial Neural Network (ANN)-based gas turbine surrogate model. The 'mission-analysis' layer is designed for multi-energy sources hybrid electric aircraft mission analysis considering fully coupled propulsion-aerodynamic effects. The 'EMS' layer utilizes non-dominated sorting genetic algorithm II (NSGA-II) addressing the design trade-off, i.e., block fuel burn, energy consumption, emissions. The proposed scheme is applied to a typical narrow-body aircraft, Boeing 737–800, equipped with mechanically integrated hybrid electric parallel propulsion configuration to explore flight electrification in civil aviation. Moreover, sensitivity analysis of battery technology level and flight mission definition is followed providing insights to hybrid electric aircraft application scenarios. The EMS optimization results indicate that for short/medium haul aircrafts which operate in high altitude with long flight durations, fuel as consumable energy source is prone to be used in initial stages to reduce aircraft weight and lift-dependent drag, while battery as non-consumable energy is optimally allocated in final flight stages of descent and landing. The design of hybrid electric aircraft is highly sensitive to both flight mission definition and battery specific energy projections. With battery specific energy projections of 1500 Wh/kg for the year 2035, optimal block fuel burn reduction by –44.62%, –31.47% and –21.86% can be obtained at the flight range design of 1000 nmi, 1250 nmi and 1500 nmi respectively.

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1. Introduction

The global aircraft fleet consumed over 7% of oil products (276 million tons of jet fuel) and produced 2.7% of energy-consumption related CO₂ emissions due to in-flight combustion [1]. Considering that global aviation demand is anticipated to grow at around 4.8% annually, it is critical to reduce the environmental footprint of the aviation industry [2]. Different organization and research councils have published pathways for reducing aviation related pollutant

emissions. For example, NASA 'N+3' aims for –75% NO_x emissions, –70% fuel burn and –55 dB noise at the airport boundary in the year of 2035 [3]. However, the potential efficiency improvements from conventional technologies progress in airframe, structure, propulsion, and air-traffic management are already reaching a plateau [4]. Thus, it is unlikely to achieve these ambitious goals through conventional technologies. Electric propulsion in aviation has emerged as a feasible solution to facilitate the environmental impacts supported by the recent progress in battery technology. Batteries can provide electrical power without direct combustion emissions, and these emissions can be alleviated effectively on the ground-based power plants, with feasible integration of clean and renewable energy sources such as solar, wind,

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and wave for the generation of electric power [5]. Additionally, electric propulsion decouples the gas turbine from propulsors and removes assembly constraints by using electrical connections, which has the potential to improve the overall propulsion system efficiency by operating fans and gas turbines at their maximum efficiency [4], while electrochemical storage systems have higher energy conversion efficiency compared to thermal ones.

However, electric propulsion development is highly dependent on electrical components and battery technology advancement. For instance, battery specific energy is projected to achieve 1500 Wh/kg in the year 2035+ [6], but even then, it will contain just 12.30% of the energy content per unit weight of jet fuel (43.9 MJ/kg). Thus, as an energy source, the battery demonstrates very low energy density, significantly increasing the weight of energy stored onboard and leading to higher drag. Batteries would also not lose mass in-flight, further penalizing their aviation application. Apart from energy storage, electric machines, power electronics, transmission and thermal management components needed for an electrical propulsion system also increase aircraft take-off gross weight, thus, a fully electric battery-powered configuration is not seen as a vital solution for commercial aviation [7]. For regional and single-aisle aircraft, hybrid-electric aircraft would be a feasible solution to make more use of electrical energy from a battery that reduces fuel burn and emissions as well as increasing the lifetime of gas turbine. Considering the state-of-the-art and projections for electric machines and battery technology will enable the adoption of hybrid-electric aircraft for medium-haul routes. Our study focuses on single-aisle hybrid electric propulsion aircraft systems [8].

The EMS for hybrid electric aircraft is a challenge. Firstly, the gas turbine fuel flow rate in-flight significantly impacts aircraft weight during flight mission, which further affects lift-dependent drag and thrust demand. Although the introduction of an electrical powertrain would improve fuel consumption and emissions performance at the propulsion system level, it might deteriorate the integrated aircraft performance due to the drag penalty. For assessing hybrid electric aircraft propulsion systems, flight segment weight change and energy balance should be considered in the mission analysis. In this context, onboard energy should be equal to mission energy demand for a defined flight mission, as an excessive amount of energy onboard would induce weight and drag penalty. This is significantly different from ground hybrid electric vehicles, given that EMS of hybrid electric aircraft explores optimum hybridization of power at each mission segment from a global optimization perspective at an integrated aircraft level. A fully coupled propulsion-aerodynamics-weight multidisciplinary model, with suitable fidelity, is required for the EMS optimization.

Existing research work on hybrid electric propulsion systems is focused on preliminary sizing and mission analysis. Sliwinski et al. [9] developed a hybrid electric propulsion system retrofit design methodology for unmanned aircraft with internal combustion and electric propulsion combination to improve endurance or flight range performance. However, the internal combustion engine performance is modelled as constant specific fuel consumption in this study. This is different from a gas turbine utilized in narrow-body or single-aisle aircraft whose gas turbine is highly sensitive to flight conditions. Sziroczak et al. [10] developed a conceptual design process for small electric and hybrid-electric aircraft with an internal combustion engine using energy fractions approach to achieve flight segment weight and energy balance through iteration, but propeller and internal combustion engine operating efficiency is only estimated by performance maps with no consideration of flight conditions. This methodology is also employed to assess small aircraft energy consumption performance in Ref. [11]. Donateo et al. [12] proposed a novel approach of assessing flight endurance of electric flight to compare fuel cell-

powered and battery-powered aircraft. However, batteries as non-consumable energy sources do not change the aircraft weight and lift-dependent drag during the flight missions, which should be considered in fuel-powered aircraft and hybrid electric aircraft. In Ref. [13], Finger et al. proposed a preliminary sizing methodology for hybrid electric general aviation aircraft based on point performance constraints and mission performance specification. However, this study holds engine specific power and efficiency as a constant value instead of a detailed gas turbine off-design performance model. In addition, this study does not account for gas turbine-electrical powertrain coupling effects. To reduce computational complexity and simultaneously ensure model accuracy, De Vries et al. [14] initially developed a methodology for hybrid electric aircraft conceptual design by generating multidimensional tables of gas turbine and propulsive device characteristics independent of the aircraft design environment, then interpolation methods are used to calculate gas turbine and propulsive device characteristics within preliminary aircraft sizing process.

EMS is to facilitate the coordinated operation of gas turbine and electrical powertrain to obtain optimal performance on fuel burn, energy consumption, and emissions considering interactions between propulsion, weight, and aerodynamics. Carlo [15] proposed energy-optimal off-design power management for a light, single-propeller hybrid electric motor glider, with limited energy availability on-board. Pernet et al. [16] developed an energy management optimization process that is simplified and performed by considering a fixed power split factor between dual-energy sources (fuel and electrical energy) for climb and cruise segments. The increased mass of the electrical powertrain and battery is accommodated by reducing payload and flight range. In Ref. [17], Ang et al. performed the EMS by looping for power-split in take-off and climb phases and optimizing and scaling down gas turbine for cruise condition for a hybrid turbofan engine powered A320 aircraft on a short-range flight mission. Furthermore, Donateo et al. [18] applied dynamic programming to obtain optimal power-split sequences. Teresa et al. [19] proposed an energy management strategy in a hybrid electric helicopter for urban air mobility to obtain the optimal usage of dual-energy sources using dynamic programming for offline optimization and equivalent consumption minimization strategy for online optimization. However, these studies are proposed based on the prior-known power demand profiles. They only investigated isolated propulsion system performance; aero-propulsive coupling effects are not considered. Ye et al. [20] proposed a fuzzy logic-based equivalent consumption optimization for hybrid electric unmanned aerial vehicles (UAVs). However, different from commercial aircraft, UAVs operate at low altitudes with short flight durations using an internal combustion engine. The performance of UAVs is not sensitive to flight conditions, energy balance, and weight-induced drag penalty will also not be a concern for lightweight UAVs. In Ref. [21], Zamboni et al. conducted a single objective optimization process with a monolithic architecture based on isolated gas turbine and aircraft mission analysis models, then manual iteration is performed between disciplines to finalize the mission analysis procedure. This also leaves design space for further optimization of EMS for hybrid electric aircraft performance. Therefore, a fully coupled propulsion-aerodynamic multidisciplinary optimization model is essential to assess and improve hybrid electric aircraft benefits with improved accuracy and computational efficiency.

This paper proposes a multi-objective optimization framework for optimum energy utilization for mission analysis level to enhance the performance of hybrid electric propulsion systems with alternative electrical energy sources. This framework comprises gas turbine performance assessment module, electrical powertrain sizing, and performance assessment module, hybrid

electric mission analysis module, and optimization algorithm module. Based on novel propulsion configuration and hybrid energy sources, the proposed framework can provide performance evaluation on fuel burn, energy consumption, emissions, and economic costs at a defined battery technology level. Feasible architecture and energy sources solutions are identified for design purposes with applications on general aviation, regional aviation, and narrow-body aircraft.

The main contributions of this paper are summarized as follows:

- 1) This paper innovatively establishes a high-fidelity ANN-based gas turbine surrogate model based on Levenberg-Marquardt back-propagation algorithm to evaluate the gas turbine performance. The ANN-based gas turbine surrogate model specifically considers the gas turbine components rematching and calculates the effect of operating point change due to electrification on engine performance and combustor inlet conditions. The proposed model can simultaneously reduce computational efforts and time for mission analysis and optimization procedures.
- 2) A methodology of mission analysis is developed for hybrid electric aircraft by considering aerodynamics, maneuver requirement, weight property, propulsion system characteristics, electrical powertrain sizing, and performance to find a solution of energy balance based on Newton Raphson method.
- 3) A fully coupled propulsion-aerodynamic optimization framework is developed based on the proposed hybrid electric aircraft mission analysis method to assess the optimal trade-off between optimization objectives including block fuel burn, energy consumption, and emissions using NSGA-II.

The remainder of the paper is organized as follows. Section II presents the proposed fully coupled propulsion-aerodynamic optimization framework and Section III introduces hybrid electric propulsion configurations and modelling and proposes performance assessment method for hybrid electric architecture. Especially, an ANN gas turbine surrogate performance model is established, which will be used in optimization procedures to reduce the computational burden. Section IV develops a methodology for hybrid electric aircraft mission analysis which takes both consumable (fuel) and non-consumable (battery) energy sources into account. Section V proposes a propulsion-mission analysis-EMS integration multi-objective optimization framework for

hybrid electric aircraft using NSGA-II algorithm. In Section VI, block fuel burn, energy consumption, and emissions performance of selected novel propulsion configuration are discussed and compared for applications on narrow-body aircraft of Boeing 737–800. Finally, the conclusions are summarized in Section VII.

2. Propulsion-mission analysis-EMS integrated multi-objective optimization framework

A propulsion-mission analysis-EMS integrated multi-objective optimization scheme is proposed to obtain optimal propulsion system performance at integrated aircraft level as shown in Fig. 1. The ‘propulsion’ layer comprises the propulsion system modelling, integration approaches, and performance synthesis using an Artificial Neural Network (ANN)-based gas turbine surrogate model. The ‘mission-analysis’ layer is designed for multi-energy sources hybrid electric aircraft mission analysis considering fully coupled propulsion-aerodynamic effects. The ‘EMS’ layer utilizes non-dominated sorting genetic algorithm II (NSGA-II) addressing the design trade-off, i.e., block fuel burn, energy consumption, emissions. The following sections will introduce each layer respectively.

3. Hybrid electric propulsion system modeling and integration

In this section, the system modelling for mechanically integrated parallel hybrid propulsion configuration (MIPH) is described. As shown in Fig. 2, MIPH consists of turbofan engine, battery stack, electric machine, power converters, and electric bus. For MIPH configuration, the battery-powered motor is mounted on the low-pressure shaft of gas turbine to drive the ducted fan. Electrical power is directly fed to the drive train of the propulsive device. The case examined herein is the B737- 800 utilizing two hybridized CFM56 turbofan engines.

3.1. ANN-based gas turbine performance model

ANNs have been widely used in gas turbine system identification and modelling, prognostics, and diagnostics because of high accuracy and lower computational efforts [22–24]. In this work, an ANN-based gas turbine performance surrogate model is developed and incorporated into aircraft mission analysis and optimization

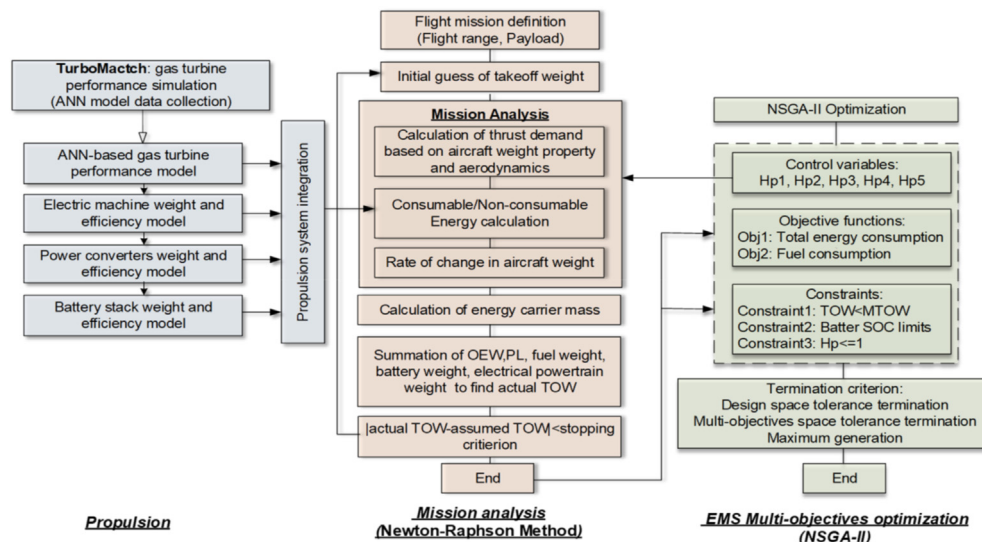


Fig. 1. Propulsion-mission analysis-EMS integrated multi-objective optimization scheme.

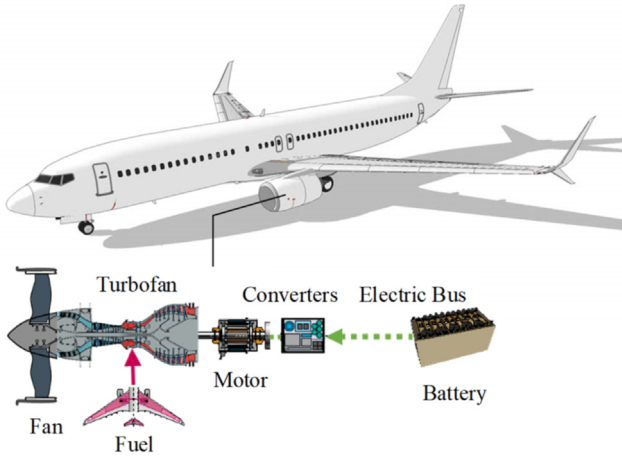


Fig. 2. The propulsion architecture of P-HEA [5].

process to reduce computational efforts and time as shown in Fig. 3.

Cranfield in-house gas turbine performance simulation software *TurboMatch* is used to produce the design and off-design performance data for the CFM56-7 engine. Table 1 reports the selected parameters of the ANN gas turbine model.

Hybridization of power on low-pressure shaft Hp_{LPT} is defined as Equation (1),

$$Hp_{LPT} = \frac{P_{on-take,LPT}}{P_{LPT}} \quad (1a)$$

where $P_{on-take,LPT}$ is power on-take of the low-pressure shaft, and P_{LPT} is power generated in low-pressure turbine.

A feed-forward multi-layer network is employed with Levenberg-Marquardt back-propagation algorithm [25] which composes of an input layer, two hidden layers and an output layer. In layer m , the output of the unit a_i can be expressed with weight

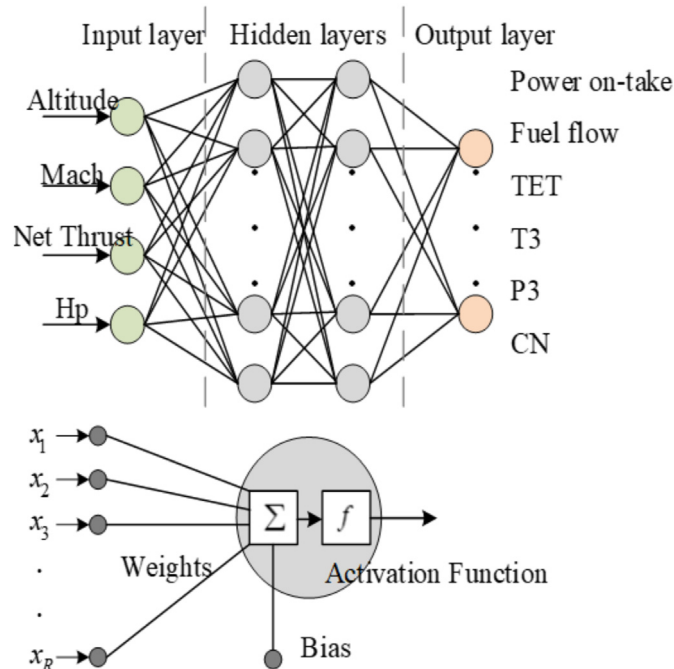


Fig. 3. ANN-based gas turbine performance model.

matrix $\mathbf{W}_i^m = [w_{i,1}^m, w_{i,2}^m, \dots, w_{i,j}^m]$, bias b_i^m , and activation function f^m as Equation (2).

$$a_i^m = f^m \left(\sum_{j=1}^S w_{i,j}^m a_j^{m-1} + b_i^m \right) \quad (2a)$$

The network system equations in the matrix form can be given by Equation (3) with input vector $\mathbf{p}$,

$$\begin{aligned} \mathbf{a}^0 &= \mathbf{p} \\ \mathbf{a}^m &= \mathbf{f}^m (\mathbf{W}^m \mathbf{a}^{m-1} + \mathbf{b}^m) \end{aligned} \quad (3a)$$

The training procedure is to learn network associations between a set of input-output pairs $\{(\mathbf{p}_1, \mathbf{t}_1), (\mathbf{p}_2, \mathbf{t}_2), \dots, (\mathbf{p}_Q, \mathbf{t}_Q)\}$ by adjusting network weights and biases until the network performance index V is minimized, as shown in Equation (4).

$$V = \sum_{q=1}^Q (\mathbf{t}_q - \mathbf{a}_q^M)^T (\mathbf{t}_q - \mathbf{a}_q^M) = \mathbf{e}_q^T \mathbf{e}_q \quad (4a)$$

About the vector-matrix of network weights and biases, the sum of squares of errors over all inputs $V(\mathbf{x})$ can be computed in Equations (5) and (6):

$$V(\mathbf{x}) = \sum_{i=1}^N e_i^2(\mathbf{x}) = \mathbf{e}^T(\mathbf{x}) \mathbf{e}(\mathbf{x}) \quad (5a)$$

$$\nabla V(\mathbf{x}) = \mathbf{J}^T(\mathbf{x}) \mathbf{e}(\mathbf{x}) \quad (6a)$$

where $\mathbf{x} = [w_{1,1}^1, w_{1,2}^1, \dots, w_{S^1,R}^1, b_1^1, \dots, b_{S^1}^1, w_{1,1}^2, w_{1,2}^2, \dots, b_{S^2}^2]^T$ is network parameter vector, R , S^m , and M refers to the number of inputs, neurons in each hidden layer and network layers respectively; $\nabla V(\mathbf{x})$ is the gradient, $\mathbf{J}(\mathbf{x})$ is the first derivatives of the network errors about the network parameter vector.

To minimize $\nabla V(\mathbf{x})$ regarding $\mathbf{x}$, Levenberg-Marquardt back-propagation method is used to update network weights and biases in Equation (7).

$$\Delta \mathbf{x} = [\mathbf{J}^T(\mathbf{x}) \mathbf{J}(\mathbf{x}) + \mu \mathbf{I}]^{-1} \mathbf{J}^T(\mathbf{x}) \mathbf{e}(\mathbf{x}) \quad (7a)$$

Then $V(\mathbf{x} + \Delta \mathbf{x})$ is recomputed using updated network parameters. The parameter μ is multiplied by β if $V(\mathbf{x} + \Delta \mathbf{x})$ is increased, otherwise μ is divided by β . The algorithm will converge when the performance index $V(\mathbf{x})$ or the gradient $\nabla V(\mathbf{x})$ reduces to performance goal and minimum performance gradient.

Besides, the coefficient of determination R^2 is introduced as Equation (8) to quantitatively evaluate the goodness-of-fit of prediction data and reference data.

$$R^2 = 1 - \frac{\sum_{i=1}^N (t_i - y_i)^2}{\sum_{i=1}^N (t_i - \bar{T})^2} \quad (8a)$$

where $T = \{t_1 \dots t_N\}$ is reference data, $Y = \{y_1 \dots y_N\}$ is prediction date, and $\bar{T}$ is the mean value of the reference date.

3.2. Electrical powertrain model

The electrical powertrain includes motor, battery stack, power converters. Aircraft-integrated performance of a propulsion system

Table 1
Gas turbine performance model parameters.

Symbol	Description	Units
H	Flight altitude	M
Ma	Flight Mach number	—
F_N	Net thrust demand	N
Hp_{LPT}	Hybridization of power on the low-pressure turbine shaft	—
$P_{on-take}$	Power on-take on low-pressure turbine	W
$\dot{W}_f$	Fuel flow rate	kg/s
T_3	Total temperature at combustor inlet	K
P_3	Total pressure at combustor inlet	Bar
T_4	Turbine inlet temperature	K
CN	Non-dimensional rotational speed of low-pressure turbine shaft	—

is particularly weight critical. Power density of conventional electrical machines is considerably low compared to gas turbine, which is considered as a key barrier to incorporate in the hybrid electric propulsion system. Recent developments in fully high temperature superconducting electric machines with extremely high-power density have made electric propulsion technology increasingly feasible. An analytical method proposed in Refs. [26–29] estimates main HTS motor parameters, e.g., specific power, mass and dimensions for massive investigations with sufficient accuracy. A parametric efficiency model is used to represent a hypothetical HTS motor that has not yet been commercially realized, however, the accuracy is feasible for preliminary studies on electrified propulsion systems [30]. Battery sizing algorithm and performance model are proposed in Ref. [31] to calculate the layout, dimensions, and weight of a battery stack over a given operating profile in a flight mission. Mass estimation and efficiency characteristics of a typical configuration of power converter are presented in Refs. [32,33]. The electrical powertrain component sizing and performance estimation are presented in Appendix.

3.3. Propulsion system integration and performance synthesis

Propulsion system performance is jointly determined by flight conditions, aerodynamics, aircraft maneuver, and gas turbine/electrical powertrain operation. A generalized propulsion system is considered with multiple propulsive devices N , assuming flight conditions $\varphi = [h, Ma]^T$, net thrust vector $\mathbf{F}_N = [F_N^1, \dots, F_N^N]^T$, energy management control policy $\mathbf{u} = [u^1, \dots, u^N]^T$.

P3T3 method [34] as a semi-empirical correlations approach is used to estimate aircraft propulsion system NOx emissions given engine internal gas path parameters at combustor diffuser inlet $\dot{W}_f, T_3, P_3$. Emission index (g CO₂/kg fuel and g NOx/kg fuel) of NOx and CO₂ caused by block fuel burn are calculated via Equations 9 and 10:

$$EI_{NOx}^i = \left(a + b \cdot e^{cT_3^i} \right) \left(\frac{P_3^i}{P_{3,ref}} \right)^d \cdot e^{f(h_{SL}-h)} \cdot \left(\frac{\Delta T_{comb}}{\Delta T_{comb,ref}} \right)^{TF} \quad (9a)$$

$$EI_{CO_2-fuel}^i = 3159 \quad (10a)$$

where default values for the constants and exponents suitable for a modern civil turbofan engine are $a = 8.4, b = 0.0209, c = 0.0082, d = 0.4, f = 19, TF = 0, P_{3,ref} = 3000 \text{ kPa}, \Delta T_{comb,ref} = 300 \text{ K}, h_{SL} = 0.006344$ [34].

Batteries can provide electrical power without direct carbon emissions, so that carbon emissions can be alleviated more effectively on the ground-based power plants, especially by increasing the utilization of clean and renewable energy sources such as

nuclear, solar, wind for electricity production. As [35], the emission index of CO₂ (g CO₂/kWh) caused by electricity production in the UK is given as Equation (11)

$$EI_{CO_2-electricity}^i = 130 \quad (11a)$$

Figure-of-Merits of hybrid electric aircraft with N thrust sources, fuel burn, total energy consumption, NOx emissions, and CO₂ emissions, can be established in Equation 12–15:

$$J_{fuel} = \int_{t=0}^{t_{end}} \left(\sum_{i=1}^N \dot{W}_f^i(t) \right) dt \quad (12a)$$

$$J_{energy} = \int_{t=0}^{t_{end}} \left(\sum_{i=1}^N \dot{W}_f^i(t) \cdot FHV + \sum_{i=1}^N \left(\frac{P_{on-take}^i(t)}{\eta_{Motor}^i(t) \eta_{Conv}^i(t) \eta_{Trans}^i(t) \eta_{Bat}^i(t)} \right) \right) dt \quad (13a)$$

$$J_{NOx} = \int_{t=0}^{t_{end}} \left(\sum_{i=1}^N EI_{NOx}^i(t) \cdot \dot{W}_f^i(t) \right) dt \quad (14a)$$

$$J_{CO_2} = \int_{t=0}^{t_{end}} \left(\sum_{i=1}^N \left(EI_{CO_2-fuel}^i(t) \cdot \dot{W}_f^i(t) + EI_{CO_2-electricity}^i(t) \cdot \frac{P_{on-take}^i(t)}{\eta_{Motor}^i(t) \eta_{Conv}^i(t) \eta_{Trans}^i(t) \eta_{Bat}^i(t)} \right) \right) dt \quad (15a)$$

where $\eta_{Motor}^i, \eta_{Conv}^i, \eta_{Trans}^i, \eta_{Bat}^i$ are the efficiency for motor, converter, transmission lines, and battery for the i -th thrust source respectively.

4. Methodology of hybrid electric aircraft mission analysis

In this section, an integrated mission analysis method for hybrid electric aircraft to evaluate novel propulsion configuration at aircraft level is proposed. Herein, an open-source credible conceptual level aircraft design platform, SUAVE, is used and extended for mission analysis of hybrid electric aircraft with advanced propulsion technologies. SUAVE provides a set of multidisciplinary analytical and semi-empirical models for aerodynamics, structures, conventional propulsion, and stability that allow augmenting relevant correlations with physics-based methods or surrogate

models [36]. A novel energy network is developed on the platform of SUAVE, where electrical system and battery stack sizing and performance model are established based on physics-based methods as described.

The flow chart of hybrid electric mission analysis is shown in Fig. 4. Aircraft mission analysis performs an iterative process for obtaining a solution of energy balance: required energy versus energy carried onboard for a specific flight mission. The flight mission profile is discretized into a large number of short flight segments. Based on the energy-based approach, the amount of both consumable energy and non-consumable energy depleted in each segment are calculated and summed up to estimate the flight mission fuel and battery mass. The iterative process is converged when the mission energy balance is satisfied.

In subsonic aircraft performance, drag is calculated as the summation of aircraft profile drag, lift dependent drag, and transonic parasitic drag by using discrete drag modules [37], which is normally expressed as Equation (16).

$$D = \frac{1}{2} \rho_0 V_e^2 S (C_{D_z} + K C_L^2) \quad (16a)$$

where D is aircraft drag, C_{D_z} is the lift independent drag coefficient, K is lift dependent drag factor, C_L is lift coefficient, ρ_0 is density at sea level ISA conditions, S is gross wing area, and V_e is equivalent airspeed. The lift coefficient is determined by aircraft flight states of angle of attack, Mach number, and flight altitude, α, Ma, h .

Aircraft dynamics in take-off phase are given in Equation (17).

$$\begin{cases} \frac{dx}{dt} = v \\ \frac{dv}{dt} = \frac{g}{W} (F_N - D - \mu R) \\ R = W - L \end{cases} \quad (17a)$$

where F_N is thrust, μ is ground friction coefficient, R is ground normal reaction, L is lift.

The dynamics equations of climb and descent phases are given with the climb or descent angle γ in Equation (18).

$$\begin{cases} 0 = L - W \cos \gamma \\ \frac{dv}{dt} = \frac{g}{W} (F_N - D - W \sin \gamma) \\ \frac{dx}{dt} = v \cos \gamma \\ \frac{dh}{dt} = v \sin \gamma \end{cases} \quad (18a)$$

The cruise phase is assumed as constant speed and constant altitude, the dynamics equations of cruise phase are given in Equation (19).

$$\begin{cases} L = W \\ F_N = D \\ \frac{dh}{dt} = 0 \\ \frac{dx}{dt} = v \end{cases} \quad (19a)$$

And aircraft weight property changes as Equation (20) according to gas turbine fuel flow rate:

$$W_i = W_{i-1} - \int_{t_{i-1}}^{t_i} \dot{W}_f dt \quad (20)$$

Aircraft weight property changes segment by segment due to the depleted consumable energy source (kerosene) which affects the lift-dependent drag in each flight segment. The weight of total consumable energy can be obtained by the integration of consumable energy in the individual segment. After that, based on a non-consumable energy-depleted profile, electrical powertrain weight and efficiency performance are sized and estimated in the opposite direction of power and energy flow. Finally, take-off weight is re-calculated as the summation of operating empty weight W_{OEW} , electrical powertrain weight W_{EP} , payload W_{PL} , fuel onboard weight W_{fuel} , and battery onboard weight $W_{battery}$ as shown in Equation (21).

$$W_{TO} = W_{OEW} + W_{PL} + W_{EP} + W_{fuel} + W_{battery} \quad (21)$$

For the iteration process, if the initial assumption or calculated

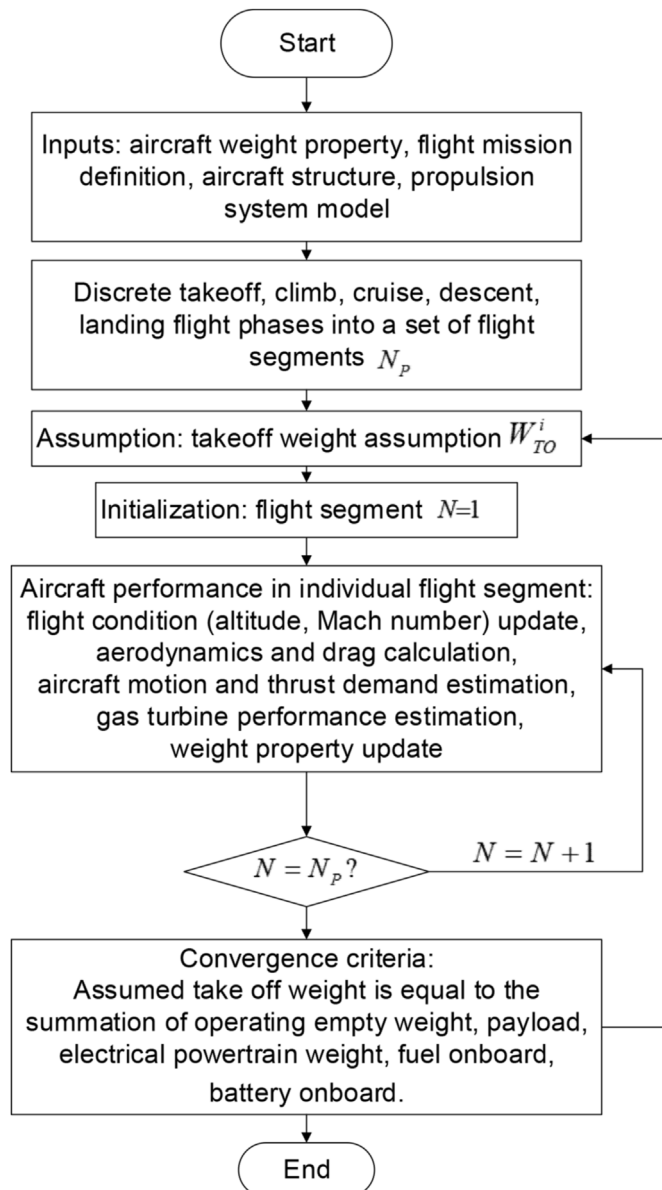


Fig. 4. Flow chart of hybrid electric aircraft mission analysis.

aircraft take-off weight does not meet the convergency criteria in Fig. 4, the mission analysis will be continuously iterated. In this study, Newton-Raphson method [38] is used for fast approximation as Equation (22):

$$x_{i+1} = x_i - \frac{f(x_i)}{f'(x_i)} = x_i - f(x_i) \frac{x_i - x_{i-1}}{f(x_i) - f(x_{i-1})}$$

$$x_i = W_{TO}^i, \quad f(x_i) = \frac{W_{TO}^i - (W_{OEI}^i + W_{PL}^i + W_{EP}^i + W_{fuel}^i + W_{Batt}^i)}{W_{TO}^i} \quad (22)$$

where x_i is iteration variable of take-off weight assumption, and $f(x_i)$ is defined as the relative error between take-off weight assumption and required take-off weight.

5. Propulsion-mission analysis-EMS integrated multi-objective optimization

In this study, the multi-objective optimization problem is solved by NSGA-II, which utilizes a fast and elitist nondominated sorting to generate a feasible set of Pareto-optimal solutions with advantages of computational burden reduction, solution spread, and efficient convergence [39]. The control variables in this study are hybridization of power for each thrust source in takeoff, climb, cruise, descent and landing flight phases respectively. The optimization objectives are block fuel burn and total energy consumption. Thus, this optimization problem can be formulated in Equation (23):

$$\mathbf{u}^* = \operatorname{argmin}(\mathbf{J}) = \operatorname{argmin} \begin{bmatrix} J_{fuel} \\ J_{energy} \end{bmatrix}$$

$$= \operatorname{argmin} \left[\begin{array}{l} \int_{t=0}^{t_{end}} \left(\sum_{i=1}^N \dot{W}_f^i(t) \right) dt \\ \int_{t=0}^{t_{end}} \left(\sum_{i=1}^N \dot{W}_f^i(t) \cdot FHV + \sum_{i=1}^N \left(\frac{P_{on-take}^i(t)}{\eta_{Motor}^i(t) \eta_{Converter}^i(t) \eta_{Trans}^i(t) \eta_{Bat}^i(t)} \right) \right) dt \end{array} \right] \quad (23)$$

$$\text{s.t.} \begin{cases} 0 \leq u^i \leq 1, \quad i = 1, 2, \dots, N & (26.1) \\ SOC_{min} \leq SOC(t) \leq SOC_{max} & (26.2) \\ W_{TOW} \leq W_{MTOW} & (26.3) \end{cases}$$

where $\mathbf{u}^*$ is optimal control vector, which indicates hybridization of power in each flight phase and are limited within [0,1]. $\mathbf{J}$ is the objective vector composed of block fuel burn J_{fuel} and total energy consumption J_{energy} .

Table 2
CFM56-7 design parameters [40].

Parameters	Value	Units
Flight altitude h	10668.0	m
Flight Mach number Ma	0.785	—
Design net thrust demand F_N	25000	N
Turbine inlet temperature T_4	1449.18	K
Air mass flow	143.94	kg/s
Bypass ratio	5.37	—
Fan DP pressure ratio	1.533	—
Fan DP isentropic efficiency	0.85	—
LP compressor DP pressure ratio	3.16	—
LP compressor isentropic efficiency	0.891	—
HP compressor DP pressure ratio	6.75	—
HP compressor DP isentropic efficiency	0.874	—
Combustion efficiency	0.999	—
HP turbine DP isentropic efficiency	0.915	—
LP turbine DP isentropic efficiency	0.926	—

6. Results and discussion

6.1. ANN-based gas turbine model validation

Cranfield in-house gas turbine performance simulation software *TurboMatch* is used to obtain turbofan engine performance for turbofan engine models CFM56-7 as training and validation datasets, which are employed in aircraft models for Boeing 737–800. The gas turbine design parameters of CFM56-7 are listed in Table 2.

To enhance the ANN network training performance, feature-wise normalization is performed in data pre-processing to process input data with each feature independently into standard

normal distribution. After that, the ANN model is trained. For data collection, both training and validation datasets cover the whole operational range of the gas turbine system. The key model parameters of the ANN model and dataset are listed in Table 3.

Fig. 5 shows model nonlinear regression performance, prediction relative error percentage for $\dot{W}_f$, $P_{on-take}$, T_3 , P_3 , T_4 , CN .

The coefficient of determination of ANN-based gas turbine

Table 3
ANN model key parameters.

Parameters	Values
Flight altitude h	[0, 11000]
Flight Mach number Ma	[0, 0.8]
Design net thrust demand F_N	[0, 25000]
Hybridization of power on LPT Hp_{LPT}	[0, 1.0]
Training/Validation	80%/20%
Neural network	MLP
Hidden layer number	2
Hidden layer neuron	20
Activation function	ReLU
Maximum Epochs	10000
Initial μ	0.001
β	10

model for $\dot{W}_f$, $P_{on-take}$, T_3 , P_3 , T_4 , CN are 0.9994, 0.9984, 0.9961, 0.9990, 0.9993 and 0.9995 respectively. The results indicate that the ANN model achieves high precision regression with low relative error.

Table 4 compares runtime of ANN-based gas turbine surrogate model and *Turbomatch* for validation dataset. The result indicates that when running for the same validation dataset, the ANN-based gas turbine performance model can save computational time by 98.60%. ANN-based gas turbine surrogate model will significantly reduce the runtime of mission analysis and optimization process.

6.2. Results of HEA sizing and mission analysis

The proposed mission analysis method for hybrid electric aircraft is applied to a typical narrow-body aircraft model, Boeing 737–800. The aircraft parameters are presented in Ref. [36]. The flight mission profile definition is given in Table 5.

The conventional aircraft performance is listed in Table 6 as benchmark.

Hybridization of power on low-pressure shaft Hp_{LPT} is assumed to be consistent in all flight phases in this subsection. Hp_{LPT} is set to range from 0.0 to 0.6 with an increment of 0.1 for dual-engine-electric with battery specific energy assumption from 1000 Wh/kg to 2500 Wh/kg.

Fig. 6 (a) and (b) present thrust demand profiles and weight

Table 4
Runtime of ANN-Based gas turbine model and *Turbomatch*.

	Runtime (s)
ANN gas turbine model	2.72233
<i>Turbomatch</i>	194.74478

Table 5
Flight mission definition.

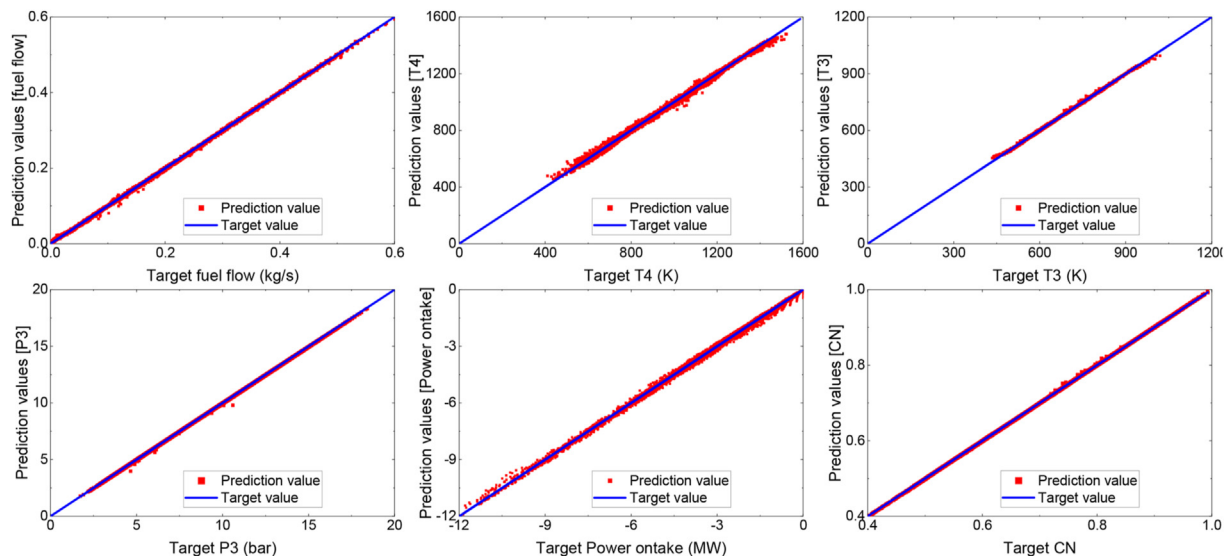
Parameter	Value
Cruise Mach number	0.785
Cruise Altitude	10668.0 m
Flight Range	2000 nmi (3704 km)
Climb Rate	6.0/6.0/3.0 m/s
Descent Rate	4.5/5.0/5.0/5.0/3.0 m/s

Table 6
Baseline design (conventional aircraft) performance.

Parameter	Value
MTOW	79015.8 kg
OEI	41140.00 kg
Payload	10000.00 kg
Battery weight	0.00 kg
Energy consumption	429075.25 MJ
Fuel burn	9769.55 kg
Fuel onboard	10258.02 kg
NOx emissions	96.19 kg
CO2 emissions	30774.08 kg

properties respectively with battery specific energy projections of 1500 Wh/kg for the year 2035. For all cases the maximum takeoff weight (MTOW) is considered as limit. When the aircraft take-off weight exceeds maximum takeoff weight, these are considered as non-applicable cases.

Fig. 7 presents parallel hybrid electric sizing and mission analysis results for dual-engine-electric operation. At the high level of Hp_{LPT} and low battery specific energy assumptions, there exists some non-applicable points where take-off weight would exceed aircraft maximum take-off weight due to electrical powertrain weight. These points are shown as blank areas in Fig. 7 (a)–(d).

**Fig. 5.** Relative error of validation datasets.

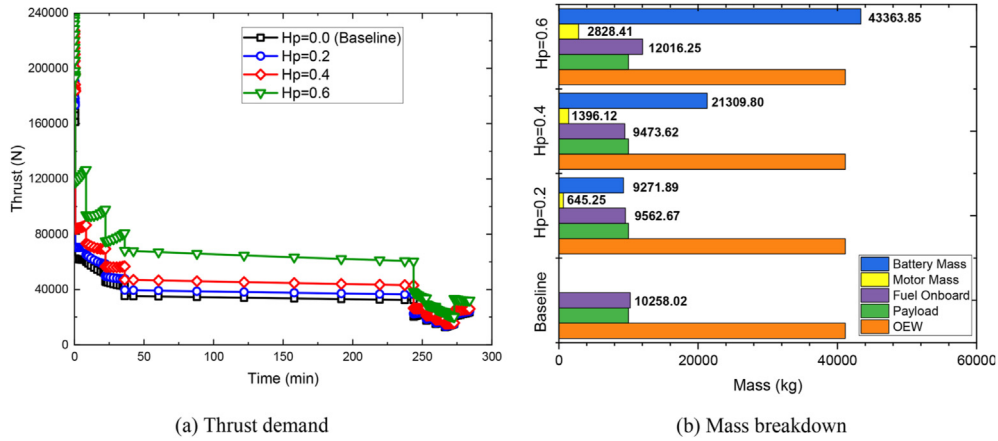


Fig. 6. Thrust demand and mass breakdown.

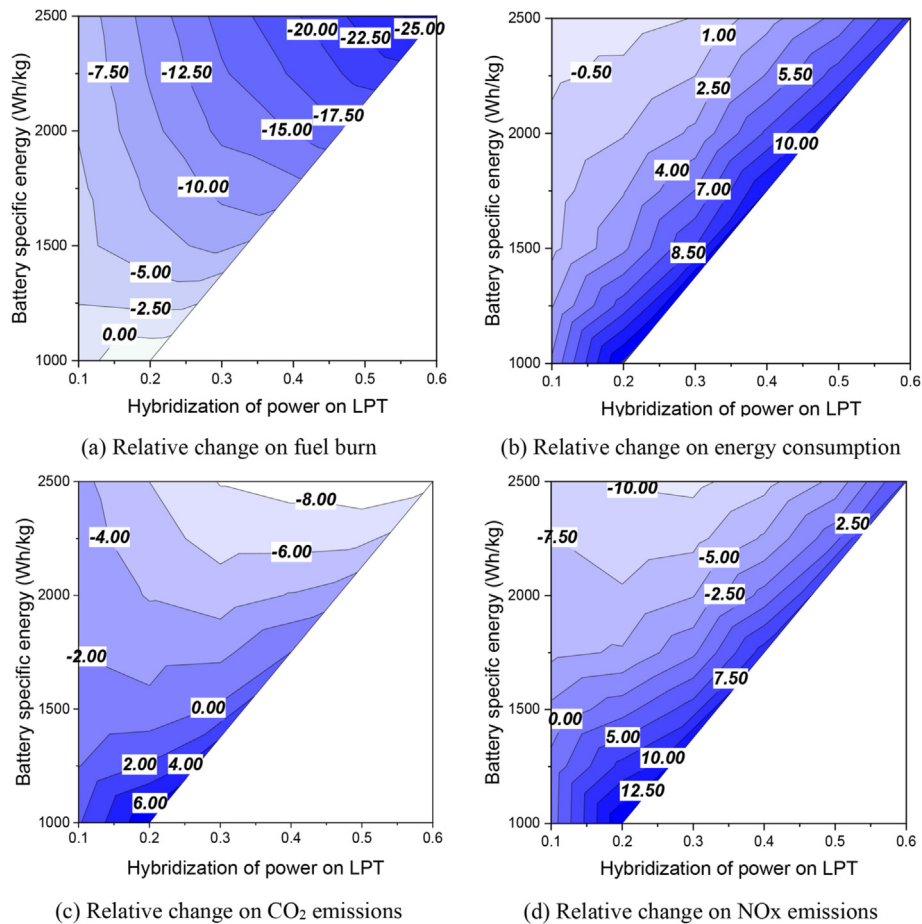


Fig. 7. Mission analysis for flight mission range of 2000 nmi.

As demonstrated in Fig. 7 (a), block fuel burn is reduced as expected due to the utilization of electrical energy. For battery specific energy of 1500 Wh/kg, significant fuel burn reduction can be achieved (-4.33% to -8.09% for 0.1 to 0.3 respectively). When battery specific energy achieves 2000 Wh/kg, block fuel burn can be further reduced by -17.5% . However, in the region of lower battery energy density, e.g., 1000 Wh/kg, block fuel burn reduction is less effective with the increase of H_{pLPT} . Because weight and drag penalty will off-set the benefit of block fuel burn reduction caused by

hybridization. In terms of fuel burn reduction, battery specific energy of around 1250 Wh/kg becomes a critical sizing criterion, below which no significant benefits can be observed by hybridization.

As shown in Fig. 7 (b), total energy consumption increases significantly following by the increase of H_{pLPT} . Even with battery specific energy of 2500 Wh/kg, energy consumption benefit cannot be achieved due to the induced weight and drag penalty if only using energy management strategy with fixed hybridization of

power in all flight phases. Given battery technology level of 1500 Wh/kg, energy consumption is estimated to increase from +0.59% to +16.44% with H_{pLPT} from 0.1 to 0.4.

The performance assessment of CO₂ emissions is shown in Fig. 7 (c). The CO₂ reduction does not follow the fuel burn reduction since the CO₂ for ground level electrical energy generation is considered herein. In the region of low battery energy density, CO₂ emissions reduction cannot be achieved because on-board carbon emissions reduction will be compromised by the ground emissions from electricity generation. The thrust demand during flight would increase accordingly due to the induced weight and drag penalty in particular with low battery energy density. For instance, given battery energy density of 1500 Wh/kg in 2035, CO₂ emissions can be slightly reduced by −1.83% if using energy management strategy with fixed H_{pLPT} of 0.1.

As shown in Fig. 7 (d), with battery specific energy of 1500 Wh/kg, NOx emission can be slightly reduced by −1.91% at H_{pLPT} of 0.1, above which NOx emissions performance degrades gradually. This is because NOx emissions are affected by both sides of gas turbine operation (T_3 and P_3) and block fuel burn. At higher level of H_{pLPT} , the benefit of block fuel burn reduction is not capable of offsetting the NOx emissions from gas turbine operation with high thrust demand and associated T_3 and P_3 .

6.3. Hybrid electric aircraft EMS optimization

As discussed, performance is not enhanced when a constant Degree of Hybridization (DoH) is applied, which is usually the case in the literature. Such simple energy management strategies, such as assuming a constant power split parameter [41,42] or a constant power setting level [43,44] does not allow the exploitation of the flexibility that hybrid propulsion offers. Thus, a computationally efficient optimization procedure is required to further investigate optimal EMS from a global optimization perspective at the integrated aircraft level. For assessing the benefits that an optimized EMS can offer the proposed optimization algorithm is applied in the following. The NSGA-II optimization algorithm is applied to the test case configuration for minimizing block fuel burn and total energy consumption for dual-engine-electric. As seen in Fig. 8 (a), different EMS selection will result in different optimal performance of fuel burn reduction (and consequently CO₂ reduction) and energy consumption reduction, highlighting the importance of EMS. It is also interesting to note that if an optimized EMS is applied there is a potential energy consumption benefit (albeit small), which is not the case for the constant DoH case.

As shown in Fig. 8, five points on the Pareto-optimal front of optimal solutions are selected to compare energy management strategy for different scenarios. S1, S2, ..., S5 represent a set of optimal performance from minimum energy consumption to minimum block fuel burn. Moving from S1 (energy saving) towards

S5 (fuel saving) scenarios, electrical energy utilization is gradually increased across all the flight phases. Within each scenario, electrical energy utilization will be prioritized from landing and descent to cruise, climb and take-off. It can be observed that for short/medium haul aircrafts which operate in high altitude with long flight durations, consumable energy (kerosene) is expected to be used in initial stages to reduce aircraft weight and avoid drag penalty. Non-consumable energy, such as electrical energy, is suggested to be allocated in the final flight phases. In addition, electrical powertrain is optimally utilized to enhance overall propulsion system performance when gas turbine operates at low efficiency region (e.g., landing, descent). In scenario of optimum block fuel burn (S5), under the constraints of maximum take-off weight, hybrid electric aircraft can achieve a maximum reduction of −19.36% for block fuel burn with the increased energy consumption of +7.83%. The CO₂ emissions and NOx emissions change by −5.65% and +3.51% respectively. In scenario of optimum energy consumption (S1), energy consumption can be slightly reduced by −0.57% with block fuel burn reduction of −3.02%, where CO₂ emissions and NOx emissions can be reduced by −1.77% and −5.52% respectively.

6.4. Sensitivity analysis of battery specific energy on EMS optimization

EMS optimization algorithm is applied to aircraft model of Boeing 737–800 to minimize block fuel burn and total energy consumption with battery specific energy assumption of 1000–2500 Wh/kg for a flight range of 2000 nmi (3704 km). In case of descent and landing phases, hybrid electric propulsion system should have ability to operate with one-engine-electric for the consideration of redundancy. In this section, both dual-engine-electric and one-engine-electric scenarios are investigated.

Fig. 9 presents Pareto-optimal fronts with assumptions on different battery specific energy. At lower value of battery specific energy considered herein, such as 1000 Wh/kg, no potential benefit on block fuel burn and energy consumption can be observed. For battery specific energy of 1500 Wh/kg, optimal block fuel burn of −8.17% and −7.69% can be observed with energy consumption increasing by +8.27% and +24.08% for dual-engine-electric (DualE) and one-engine-electric (OneE) respectively. However, potential benefits on energy consumption cannot be observed across all battery specific energy assumptions. At the same battery specific energy, optimal block fuel burn reduction for one-engine-electric operation in descent and landing degrades slightly compared with dual-engine-electric, however the significantly higher energy consumption penalty can be observed.

Fig. 10 shows NOx emissions performance of Pareto-optimal fronts with different battery specific energy. NOx emissions can be reduced by −3.66%, −4.23%, −8.43% and −10.92% for battery specific

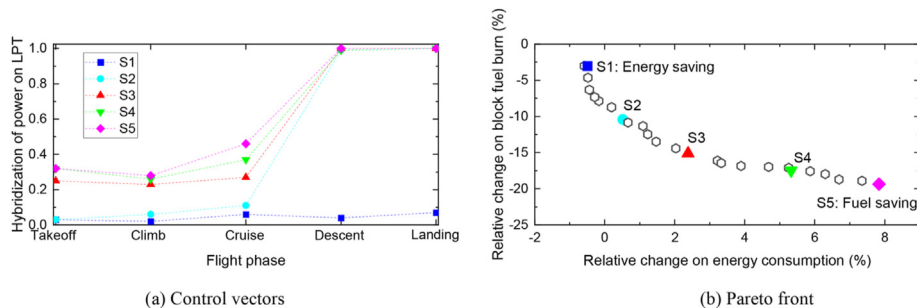


Fig. 8. Multi-objective optimization results for flight range of 2000 nmi.

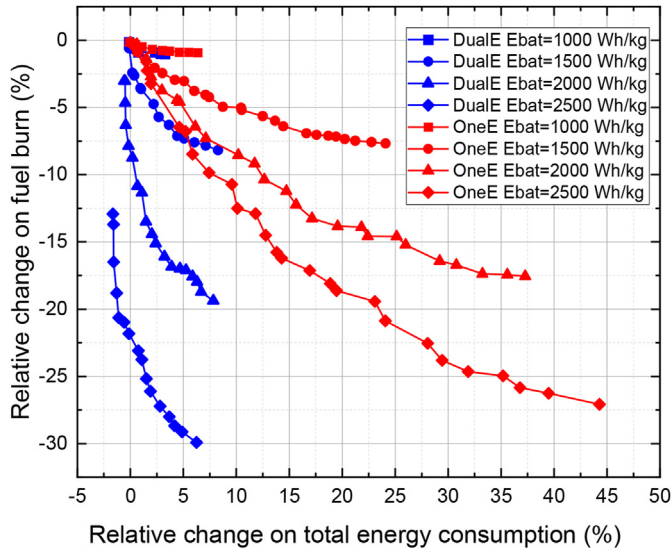


Fig. 9. Pareto-optimal fronts for flight range of 2000 nmi (3704 km).

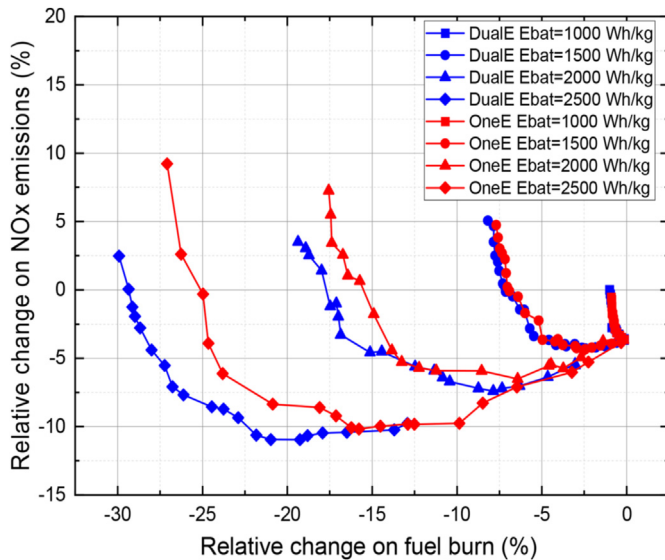


Fig. 10. NOx emissions of pareto-optimal front for flight range of 2000 nmi (3704 km).

energies of 1000, 1500, 2000, and 2500 Wh/kg for dual-engine-electric operation. For the case of one-engine-electric operation for redundancy, the maximum benefit in terms of NOx emissions reduction that can be achieved is -3.85% , -4.92% , -6.51% and -10.16% respectively for battery specific energies of 1000, 1500, 2000, and 2500 Wh/kg. NOx emissions decrease initially due to block fuel reduction but then increase again. This is because electrical energy has a greater share in hybridization with the reduced fuel burn, which will subsequently increase the electrical powertrain weight and aircraft thrust demand, which means that the engine will work at higher combustor inlet temperature and pressure throughout the mission. In addition, minimum NOx emissions on Pareto front of one-engine-electric operation are slightly higher than that of dual-engine-electric operation.

Relative changes in CO₂ emissions of pareto-optimal fronts are shown in Fig. 11. Similar to NOx emissions trend, potential CO₂ emissions reduction does not always follow the trend of block fuel burn reduction. Following by the fuel burn reduction, CO₂

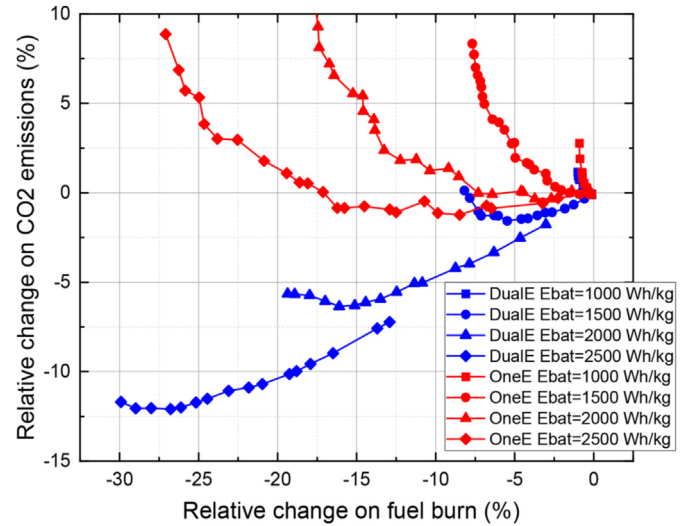


Fig. 11. CO₂ emissions of pareto-optimal front for flight range of 2000 nmi (3704 km).

emissions will initially reduce, then slightly increase in dual-engine-electric but massively increase in one-engine-electric operation. The main reason is that the additional weight of electrical powertrain would induce weight-related drag penalty and significantly increase the thrust demand due to sizing cascading effects. Herein, the CO₂ emissions from installed battery energy storage is considered, which is caused by electrical energy production in the power grid. With the increasing level of hybridization, the sizing cascading effects and drag penalty are accordingly increased and become a major concern, the reduced CO₂ emission by engine is not capable of offsetting the increased emission production by the power grid. Especially for one-electric-engine operation, no promising CO₂ emissions reduction can be seen even with high battery specific energy assumption. For the same fuel burn reduction, much higher electric energy is required for one-engine-electric operation, which will eventually lead to much higher CO₂ emissions. In contrast, dual-engine-electric operations can effectively reduce CO₂ emissions by -0.04% , -1.57% , -6.35% and -12.08% at most for battery specific energy from 1000 Wh/kg to 2500 Wh/kg.

6.5. Sensitivity analysis of flight mission on EMS optimization

In this section, sensitivity analysis of flight range to the integrated aircraft performance is conducted. Table 7 lists baseline design aircraft performance with specific flight range parameters.

Fig. 12 shows a set of Pareto-optimal front of block fuel burn and total energy consumption with battery specific energy of 1500 Wh/kg for different flight missions. It can be found that the potential benefit of energy consumption and block fuel burn reduction of short flight range missions are superior to that of long range. With flight range of 1000 nmi (1852 km), optimal fuel saving of -44.62% and -37.98% can be obtained for dual-engine-electric and one-

Table 7
Baseline aircraft performance with different flight range.

Flight range/nmi	Fuel burn/kg	Energy/MJ	CO ₂ /kg	NOx/kg
1000	4994.78	219413.33	15733.56	49.21
1250	6166.59	270860.70	19424.76	60.60
1500	7362.94	323387.77	23193.26	72.39
1750	8586.22	377106.97	27046.59	84.63
2000	9769.55	429075.25	30774.08	96.19

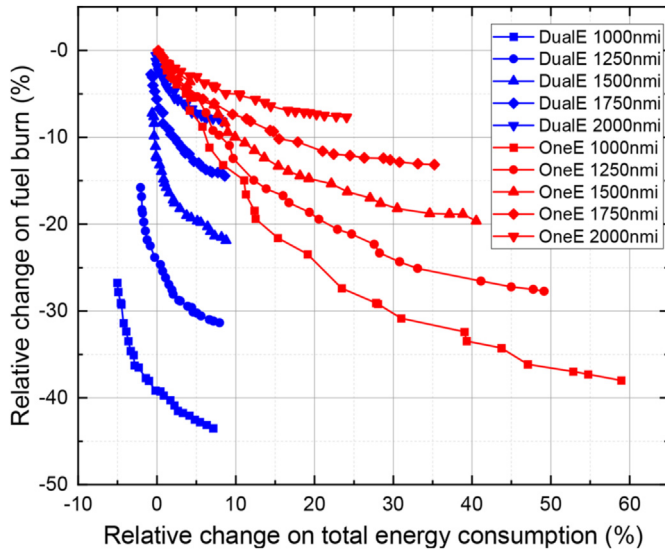


Fig. 12. Pareto-optimal front for battery specific energy of 1500 Wh/kg.

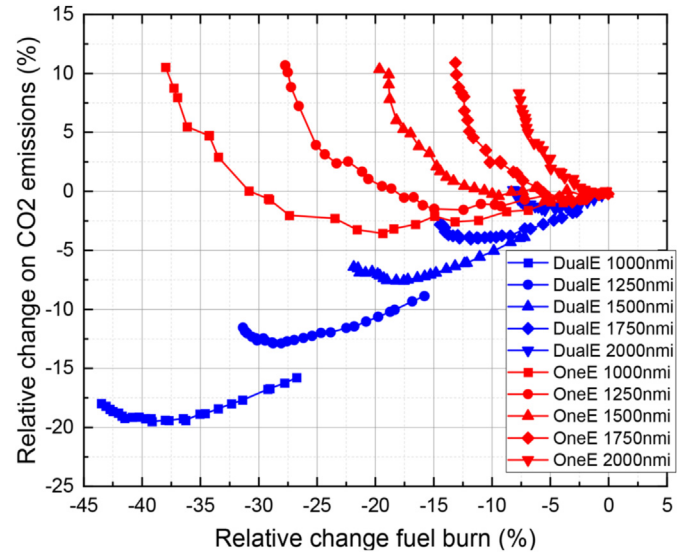


Fig. 14. CO₂ emissions performance of pareto-optimal front for battery specific energy of 1500 Wh/kg.

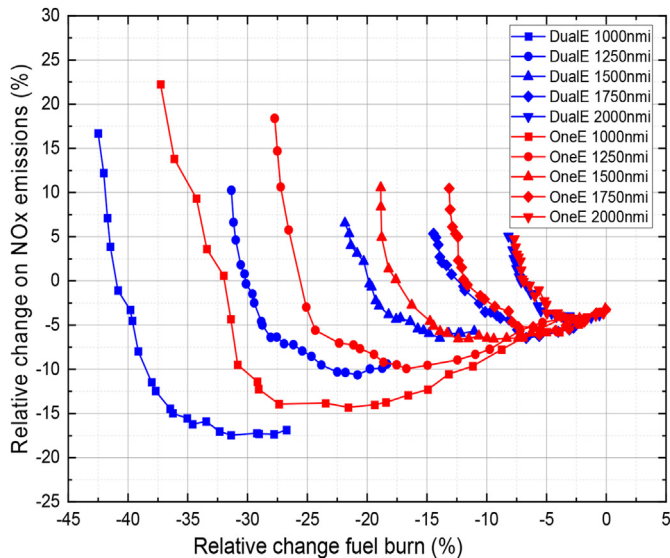


Fig. 13. NO_x emissions performance for pareto-optimal fronts for battery specific energy of 1500 Wh/kg.

engine-electric operations respectively. The benefits of block fuel reduction and energy consumption reduce gradually with the increase of flight ranges. For flight range of 2000 nmi (3704 km), no potential benefit on energy consumption can be expected while the maximum fuel burn reduction is less than -10% . This is because take-off gross weight of short-range flight mission is much lower than that of long-range flight. Therefore, more design space is available to accommodate additional weight of electrical powertrain and battery stack onboard. Besides, sizing cascading effect for short-range flight mission is relatively lower than that of long-range flight.

In terms of NO_x emission of Pareto-optimal fronts shown in Fig. 13, the highest NO_x emissions reductions of -17.56% and -13.95% are achieved for dual-engine-electric and one-engine-electric operation respectively when flight range is defined as 1000 nmi (1852 km). However, with flight range of 2000 nmi (3704 km), only -4.24% and -4.33% can be observed for maximum

NO_x emission reductions. It can be observed that the result shows a convex curve relationship between block fuel burn reduction and NO_x emission reduction. For example, for flight range of 1000 nmi (1852 km) with dual-engine-electric operation, NO_x emissions decrease gradually with the block fuel burn reduction to a minimum value when the block fuel burn reduction reaches -31.38% . After this turning point, the NO_x emissions start to increase following by the further reduction on block fuel burn. For short flight range missions, the performance of NO_x emissions reduction becomes more effective comparing with long flight range missions. For long flight range over 2000 nmi (3704 km), there is no obvious benefits for either NO_x emission or block fuel burn reductions.

The relative changes on CO₂ emissions for pareto-optimal fronts are shown in Fig. 14. For dual-engine-electric operation, CO₂ emissions reduction can be achieved across all flight ranges with the reduced fuel burn and increased electrical energy utilization. Potential benefits of CO₂ emissions reduction for short-range flight mission are more effective than long-range flight mission. Maximum CO₂ emissions reduction of -19.38% can be obtained with flight range of 1000 nmi (1852 km), but only -1.57% for flight range of 2000 nmi (3704 km). It is worthwhile noting that CO₂ emissions will initially reduce but increase slightly against the reduced block fuel burn when block fuel burn reduction is close to maximum capacity. For one-engine-electric operation, maximum CO₂ emissions reduction is relatively low, even for short-range flight missions, the relative changes on CO₂ emissions are within -5% . For long-range flight mission, the benefits of CO₂ emissions reduction become less effective as compared to short-range flight mission. This is because the aircraft takeoff weight of short-range flight mission is relatively lower than that of long-range flight mission. Given the constraints of aircraft maximum takeoff weight, more design space is available for HEA with short range flight mission to accommodate electrical powertrain and onboard battery energy storage. Besides, sizing cascading effect is also a major concern for HEA with long range flight mission, which would significantly induce weight-related drag penalty and increase the thrust demand accordingly. For one-engine-electric operation, the potential benefits of CO₂ emissions reduction are not as competitive as dual-engine-electric operation. This is because for the same fuel burn reduction level, much higher electrical energy from onboard battery energy storage is required for

one-engine-electric operation, which will result in relatively higher ground CO₂ emissions from electrical energy generation in power grid.

7. Discussions

In this section, the proposed mission analysis method is applied to Boeing 737–800 with a fixed hybridization of power during whole flight mission to evaluate parallel hybrid electric propulsion configuration at integrated aircraft level. It can be concluded that for the performance of fuel burn reduction, battery specific energy of around 1250 Wh/kg becomes a critical sizing criterion for flight range of 2000 nmi (3704 km), below of which no significant benefits on block fuel burn reduction can be observed. For low battery specific energy assumption, fuel burn reduction benefits degrade with higher level of hybridization of power. NOx emissions are affected by both sides of gas turbine operation (T3 and P3) and block fuel burn. With high level of hybridization of power, the benefit of gas turbine power on-take, and reduced block fuel burn are not capable of offsetting the sizing related drag penalty and highly increased thrust demand.

For a dynamic hybridization of power strategy, multi-objective optimization using NSGA-II is adopted to establish an optimal EMS to minimize block fuel burn and energy consumption for flight range of 2000 nmi (3704 km). The EMS is applied to different battery specific energy scenarios for sensitivity analysis of battery technology level. Optimal block fuel reduction of –8.17%, –18.85% and –29.17% can be achieved at battery specific energy of 1500 Wh/kg, 2000 Wh/kg and 2500 Wh/kg for dual-engine-electric operation, with increased energy consumption penalty of +8.5%, +7.9% and +6.25% respectively. A trend can be observed that fuel as consumable energy source is prone to be used in initial stages to reduce aircraft weight and lift-dependent drag, while battery as non-consumable energy is optimally allocated in final flight stages of descent and landing.

Sensitivity analysis of flight mission range is performed based on battery specific energy projections of 1500 Wh/kg. Optimal block fuel burn reduction from –44.62% and –21.86% can be obtained at flight range of 1000 nmi (1852 km) and 1500 nmi (3704 km) respectively for dual-engine-electric. At flight range of 1000 nmi (1852 km), optimal energy consumption reduction of –5% can be expected with fuel burn reduction of –26.71%. Potential benefits of block fuel burn reduction and energy consumption reduction degrade with the increased flight range. When flight range exceeds 2000 nmi (3704 km), no benefits on energy consumption can be observed and maximum fuel burn reduction is less than –10%. Sensitivity analysis results of fuel burn reduction, CO₂ emissions reduction change significantly for different sets of flight ranges and battery specific energy levels even for the same aircraft model. Thus, the design of hybrid electric aircraft is highly sensitive to both flight mission definition and battery technology level.

8. Conclusion

This paper proposed an optimization framework for hybrid electric aircrafts. The particular aspect was to assess and improve block fuel burn, energy consumption and emissions performance considering the propulsion-aerodynamics coupled effect. Firstly, an ANN gas turbine surrogate performance model was established and integrated with the EMS optimization procedure to ensure computational efficiency and high fidelity. The electrical powertrain weight and efficiency were established upon physics-based models. Then, mission analysis approach is developed to accommodate electrical powertrain and battery energy storage by discretizing the flight mission segment. Ultimately, an NSGA-II based

multi-objective optimization algorithm is utilized to identify optimized hybridization of power in individual flight phase (i.e., minimizing block fuel burn and energy consumption). NOx emissions performance is assessed by using a semi-empirical correlations approach of ‘P3T3’ method, while CO₂ emissions comprise both in-flight and power grid through carbon emissions index. The EMS optimization results indicate that fuel as consumable energy source is prone to be used in initial stages to reduce aircraft weight and lift-dependent drag, while battery as non-consumable energy is optimally allocated in final flight stages of descent and landing. Sensitivity analysis results of fuel burn reduction, CO₂/NOx emissions reduction will change significantly for different sets of flight ranges and battery specific energy level. As a result, the design of hybrid electric aircraft is highly sensitive to both flight mission definition design and battery specific energy projections. The benefits of short-range flight mission on block fuel burn, energy consumption and emissions are superior to that of long-flight range missions. In terms of emissions performance, both CO₂/NOx emissions show a convex curve relationship between block fuel burn reduction and emission reduction due to sizing cascading effects.

Credit author statement

Jinning Zhang: Writing – original draft, Methodology, Formal analysis, Software, Investigation, Formal analysis, Validation. **Ioannis Roumeliotis:** Writing – review & editing, Supervision, Investigation. **Argyrios Zolotas:** Writing – review & editing, Supervision, Investigation.

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.

Appendix

A. Fully high temperature superconducting motor model

An analytical method proposed in Refs. [27–29] estimates main HTS motor parameters, e.g., specific power, mass and dimensions for massive investigations with good accuracy. The methodology is based on torque per unit of rotor volume:

$$TRV = \frac{T}{V_m} = \frac{\pi}{\sqrt{2}} k_{w1} AB \quad (1b)$$

where k_{w1} is winding factor, A is electrical loading and B is average flux density, V_m is the volume calculated by mean stator winding diameter for fully HTS electric machine. The definition of mean stator factor is:

$$m = \frac{R_m - R_r}{R_s - R_r} \quad (2b)$$

where R_m is mean stator radius, R_s is outer stator radius, and R_r is outer rotor radius, R_s can be derived as follows:

$$R_s = \frac{\left(\frac{a \cdot R_m}{1-m}\right) + b}{1 + \frac{m \cdot a}{1-m}} \quad (3b)$$

where a represents rotor and stator linear factor, and b represents rotor and stator adding factor which are fitted based on a survey on interior-rotor electric machines.

The total weight can then be estimated as follows:

$$W = \frac{\pi}{4} D_s^2 L_a \rho (1 + \alpha) \quad (4b)$$

where L_a is active length, ρ is electric machine active density and α is cryostat weight factor.

To estimate electrical machine efficiency, a parametric efficiency model is used to represent a hypothetical HTS motor [27]. The motor efficiency is calculated as Equations (5)–(7):

$$\eta_{Mot} = \frac{P_{Motor}}{P_{Motor} + P_{Loss}} = \frac{w \cdot Q}{w \cdot Q + P_{Loss}} \quad (5b)$$

$$P_{Loss} = C_0 + C_1 w + C_2 w^3 + C_3 Q^2 \quad (6b)$$

$$C_0 = k_0 \frac{\hat{w} \hat{Q}}{6} \frac{1 - \hat{\eta}}{\hat{\eta}}, \quad C_1 = \frac{-3C_0}{2\hat{w}} + \frac{\hat{Q}(1 - \hat{\eta})}{4\hat{\eta}} \quad (7b)$$

$$C_2 = \frac{C_0}{2\hat{w}^3} + \frac{\hat{Q}(1 - \hat{\eta})}{4\hat{\eta}\hat{w}^2}, \quad C_3 = \frac{\hat{w}(1 - \hat{\eta})}{2\hat{Q}\hat{\eta}}$$

where η_{Mot} denotes motor efficiency, ω is motor rotational speed, Q is torque and P_{Loss} is power loss, C_i is served as the constants of proportionality for each loss term, k_0 serves as a convenience factor for specifying a parametric motor model, $\hat{\eta}$, $\hat{w}$, $\hat{Q}$ are peak efficiency, peak efficiency speed and torque.

B. Battery sizing and performance model

Battery sizing algorithm and performance model are proposed in Ref. [31] to calculate the layout, dimensions, and weight of a battery stack over a given operating profile. The sizing algorithm uses design power load P_{Design} and current operating profile $i(t)$ as inputs.

Firstly, the number of battery cells in parallel is determined as Equation (8) based on total energy discharged over the profile.

$$N_{parallel} = \frac{\int_{t=0}^{t_{end}} i(t) dt}{k_2 \cdot Q_N \cdot (1 - q_L)} \quad (8b)$$

where Q_N is nominal capacity of battery cell, q_L is charge reserves.

Then, the capacity discharged before design power load $Q_{dis,bat,P}$ is calculated as Equation (9):

$$Q_{dis,bat,P} = \int_{t=0}^{t_p} \frac{i(t)}{N_{parallel}} dt \quad (9b)$$

After that, battery cell performance model is wrapped into sizing procedure to estimate voltage output as Equation 10–12 :

$$E_P = k_1 \cdot E_0 - k_2 \cdot K \cdot \frac{k_3 \cdot Q_N}{k_3 \cdot Q_N - Q_{dis,bat,P}} + (k_4 \cdot A) e^{-k_5 \cdot B \cdot Q_{dis,bat,P}} \quad (10b)$$

$$i_{bat,P} = \frac{i(t_p)}{N_{parallel}} \quad (11b)$$

$$V_{bat,P} = E_P - k_6 \cdot R \cdot i_{bat,P} \quad (12b)$$

The battery cell power output at design power load is shown as Equation (13),

$$P_{bat,P} = V_{bat,P} \cdot i_{bat,P} \quad (13b)$$

Then, the battery stack layout can be determined as Equations 14 and 15:

$$N_{cells} = \frac{P_{Design}}{P_{bat,P}} \quad (14b)$$

$$N_{series} = \frac{N_{cells}}{N_{parallel}} \quad (15b)$$

Finally, battery stack weight and volume can be determined based on battery specific energy ρ_{energy} and power density ρ_{power} and nominal voltage of battery cell V_N as Equations 16 and 17.

$$W_{bat} = \frac{N_{cells} \cdot V_N \cdot k_2 \cdot Q_N}{\rho_{energy}} \quad (16b)$$

$$Vol_{bat} = \frac{P_{bat,P} \cdot N_{cells}}{\rho_{power}} \quad (17b)$$

And battery efficiency can be calculated as Equation (18):

$$\eta_{Bat}(t) = 1 - \frac{i(t)_{bat}^2 R}{U_{bat,oc}(t) i_{bat}(t)} \quad (18b)$$

And battery state of charge (SOC) can be estimated as Equation (19):

$$SOC(t) = SOC(t_0) - \frac{\int_{t=0}^t i(t) dt}{Q_{Bat}} \quad (19b)$$

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