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Thermal Management System Modeling and Architectures for Conceptual Design of Electrified Aircraft

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Electrified aircraft designs require thermal management systems (TMS) to maintain all electric propulsive components at safe operating temperatures. Modeling the TMS for inclusion in the study of such aircraft from the early stages of conceptual design is required to properly evaluate the feasibility and performance of such aircraft configurations. This work presents a tool-agnostic, multifidelity TMS modeling methodology that is capable of representing TMS architectures in a unified way. The methodology is implemented in an existing MDAO framework, which is built on top of NASA's Aviary aircraft design code and OpenMDAO. The results are validated against literature for several aircraft size classes. The impacts of TMS architectures and subsystem performance parameters on aircraft weight, drag, and power consumption are presented. Trade studies show that ducting losses, heat acquisition effectiveness, plumbing layout, and electrification factor are major influences of system level performance. Neglecting these effects during early design stages can create additional challenges to realizing the benefits of electrification at later design stages.

I. Introduction

ELECTRIFIED aircraft concepts have the potential to reduce fuel burn across a range of contemporary missions. Due to the limitations of modern battery technology, which may prevent entirely electric flight depending on mission requirements, a variety of electrified propulsion architectures are considered. In recent years, design studies for electrified aircraft have matured to the point of considering subsystem requirements beyond those of the powertrain. As electrified propulsion components are often temperature sensitive, thermal management systems (TMS) are required to keep batteries, motors, and power electronics within safe operating limits.

Research shows that appropriate aircraft propulsion architecture is a function of mission requirements. NASA SUSAN and STARC-ABL concepts use turboelectric propulsion architectures, and they are intended as electrified alternatives for the single-aisle commercial airliner market [1, 2]. Cinar et al. [3] show that a parallel hybrid propulsion architecture can reduce block fuel for the thin-haul and regional aircraft classes, provided optimal system operations. Private companies have already developed general aviation class aircraft which have taken flight, including Electra.aero [4], Joby Aviation [5], and Harbour Air [6]. The NASA X-57 Maxwell, while never airborne, advanced knowledge of energy source-propulsion design synergy, showing that electric energy can be fully taken advantage of through a high-lift distributed propulsor arrangement [7, 8].

Because various electrified propulsion components generate different “grades” of waste heat, which may necessitate unique cooling strategies [9], a given propulsive architecture will require a suitable TMS for its specific needs. Existing studies often select a mission profile and subsequently assume a known thermo-propulsive architecture before aircraft sizing. The X-57 used an air-cooling system for its motors to “maintain design simplicity” [10]. Later conceptual

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studies by Brelje et al. [11] and Adler et al. [12] size and optimize TMS design parameters for an electrified concept. Byahut and Uranga [13] developed models for a TMS using a fixed architecture, and the system-level effects for a 19 passenger aircraft under a static aircraft weight assumption were studied. Similarly, Shekar and Clarke [14] study battery performance under ambient temperature changes, sizing a battery TMS under an assumed architecture for a 19 passenger thin-haul aircraft.

According to Jensen et al. [15] domestic flights in the United States accounted for 69% of aviation carbon emissions in 2019. Single-aisle aircraft are an attractive target class for electrification in the future because they often fly domestic routes with generally shorter ranges. Current literature on detailed TMS design for single-aisle class aircraft is limited to a few concepts with custom designed systems. The SUSAN [1], STARC-ABL [2], Boeing SUGAR-Volt [16], and AEA-800 [17] concepts would all compete with aircraft such as the Airbus A320 and Boeing 737, which are popular choices for the single-aisle market. These studies include preliminary weight estimates for TMS, but do not consider power draws required by the cooling systems, nor are the TMS weights actively scaled as the designs are sized. More recent SUSAN literature [18] details TMS modeling and architecture, however, this approach is specific to the SUSAN not generalized to any conceptual design. The interest in electrified concepts for the single-aisle market necessitates the need for rapid advanced concept development with TMS modeling capability across a range of aircraft classes and mission profiles.

Prior work has demonstrated conceptual thermal-management modeling, sizing, and optimization for electrified aircraft, and in some cases has compared multiple thermal architectures. However, these studies generally either assume a fixed thermal topology, examine a limited set of architectures for a specific aircraft class, or do not expose analytic sensitivities within a mission-level aircraft MDAO environment. The present contribution is therefore a methodology for a modular, component based TMS sizing and performance evaluation, flexible with respect to aircraft class and propulsion architecture, suitable to evaluate and validate electrified concepts which intend to compete with conventional aircraft in a variety of markets. The approach supports centralized and distributed, passive and active, and air- and fuel-rejecting architectures within an optimization ready representation.

This paper is a part of a series of research papers intended to outline the aircraft MDAO framework developed under the NASA AACES 2050 initiative, introduced in Mahseredjian and Vascik [19] and Kaneko et al. [20]. This work is directly integrated into the updated MDAO framework described in Hajdik et al. [21], and Sebastian et al. [22].

II. Methodology

This section will discuss the philosophy behind the TMS methodology’s capabilities as well as the technical implementation for the TMS architecture encoding, the KPP-driven approach, and the implementation within a larger optimization framework.

A. TMS Architectures

This work discusses the development of the TMS method and integration into the aircraft design framework. Future work will study optimal TMS architectures as a function of propulsive architecture. Examination of current literature shows that several characteristics would be required for the design of a comprehensive TMS modeling strategy. Both passive and active cooling need to be represented. In other words, the TMS should be able to accommodate architectures where coolant directly flows from source to sink, as well as architectures where a heat pump cools the flow back to the source, heating the flow to the sink. This architecture may be desirable in cases where heat producers need to be kept at low temperatures where they generate “low-grade” heat. Heat sinks are ultimate destinations where the heat generated aboard the aircraft is rejected. The TMS incorporates the ability to reject heat to an internal reservoir (i.e. any fuel that may be on the aircraft) or to ambient air. It assumes that heat is transported internally through a liquid coolant. Additionally, the TMS allows components to be connected in series, where coolant exiting a heat source flows into another before rejecting heat to a sink. In the case that a heat source needs to be kept cooler than another, it may benefit from being “first-in-line” in the architecture. Because components are modeled independently, the flexibility allows the impact of component ordering to be explored.

A TMS architecture modeled in this work is described through a directed adjacency matrix, henceforth referred to as an “architecture” matrix, symbolized as A . It is a square matrix of size n by n , where n is the number of components in the thermal management system. A connection between component i and j is indicated by $A_{ij} = 1$, and represents a direct flow of coolant from component i to component j . Connections which are not present use 0 as an indicator of component separation. Note that this setup ignores final sink-to-source return connection to avoid cyclic behavior internally. Fortunately, it is trivial to trace a path upstream or downstream within an architecture to produce the exact

index of each of the components connected to a component of interest. “Components” are elements of any TMS which are categorized as heat sources, heat pumps, or heat sinks. Elements such as plumbing and fluid pumps are not neglected (see the following section) but are assumed inactive from a thermodynamic perspective, and thus are not included in the TMS architecture matrix. A component-type key is a vector of flags which identifies each of the components in the system; it is necessary to distinguish between components to ensure the correct model as the designer intends. This work uses the following conventions: the key is symbolized as c , it is of size 1 by n , and components are identified by a 0 for heat producers, a 1 for heat pumps, a 2 for heat sinks which reject heat to an internal coolant reservoir, or a 3 for heat sinks which reject heat to the atmosphere. Figure 1 provides examples of architectures and their corresponding matrices and keys.

As illustrated in Fig. 1, this methodology enables the sizing of any thermal architecture, capturing powered and unpowered, centralized and distributed, and internal and atmospheric cooling systems. This capability is essential as these design decisions greatly impact performance of electrified aircraft at the system level.

B. Forward Temperature Solve and Closure Enforcement

With an architecture defined, it is possible to solve for the temperature of a coolant (or in the case of a two-phase loop, a refrigerant) at each point of interest within the TMS. Specifically, these points of interest are the outlets of each heat producing component, which must be kept below some maximum temperature. These temperature constraints are enforced at the optimization level, discussed in the following section. The role of the temperature solver is to enforce a closed thermodynamic cycle, evaluate the various subsystem outputs, and to evaluate their gradients as well. The inputs and outputs of the temperature solver are shown in Table 1.

Table 1 Temperature solve input-output space. Static values are shown in *italics*, the gradients of which are not computed as they represent parameters which an optimizer will not control.

Inputs	Outputs
Coolant and Refrigerant Mass Flow(s)	Component Inlet Temperatures
Component Heat Generation	Component Outlet Temperatures
<i>Coolant and Refrigerant Specific Heat</i>	Fuel Heating Rate
<i>Heat Acquisition Effectiveness</i>	
<i>Heat Rejection Effectiveness</i>	
Heat Pump Return Temperature(s)	
Initial Coolant and Refrigerant Temperature(s)	
Fuel Mass	
Fuel Temperature	
Ambient Temperature	

Specific heats and effectiveness are static because an optimizer would exploit its control over these values, designing an unrealistic system. The coolant and refrigerant mass flows are the variables which control how much heat can be exchanged throughout the TMS, setting the inlet and outlet temperatures of each component. Because the temperature limits are enforced at the optimization level, the mass flows are also varied at that level. The temperature solver varies the assumed initial temperature of each closed coolant or refrigerant loop such that the final temperature returns to the initial value. This solve is required as the final temperature is implicit in its own calculation (i.e. $T_{\text{final}} = f(T_{\text{final}}, \dots)$). The ambient and fuel temperatures determine the heat rejection at the heat sinks, and the fuel mass is used to calculate the rate of fuel heating, which is integrated over time to track the fuel temperature. This is necessary to determine the reduced cooling capabilities as the fuel heats, as well as to ensure the fuel remains below a maximum safe operating temperature. Figure 2 highlights where the initial and final loop temperatures exist within notional TMS cycles.

The following subsections will detail the functional and gradient evaluation of the inlet and outlet temperatures within a given TMS. The temperature solver utilizes the architecture matrix to forward propagate values to the correct downstream component. This ensures that no matter the architecture’s complexity, correct values are always computed.



$$A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad c = [0 \quad 1 \quad 3]$$

(a) Example powered air-cooling.



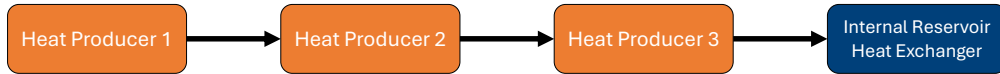
$$A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \quad c = [0 \quad 1 \quad 2]$$

(b) Example powered internal-cooling.



$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad c = [0 \quad 3 \quad 0 \quad 3]$$

(c) Example distributed passive air-cooling.



$$A = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad c = [0 \quad 0 \quad 0 \quad 2]$$

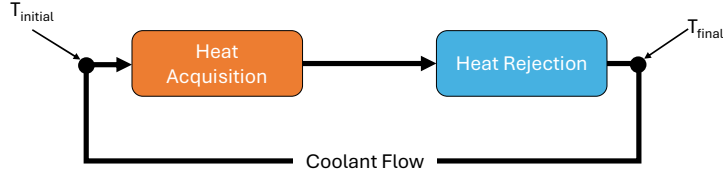
(d) Example passive internal-cooling with components in series.

Fig. 1 Example thermal management architectures and their corresponding matrices and component keys.

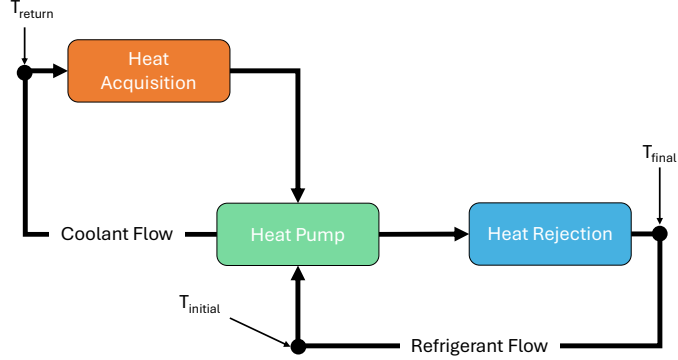
1. Evaluation and Gradients of Heat Producing Components

The coolant temperature rise across a heat producing component is given in Eq. 1 as

$$T_{i,\text{out}} = T_{i,\text{in}} + \frac{\dot{Q}_i}{\epsilon_i \dot{m}_j c_{\text{coolant}}} \quad (1)$$



(a) Notional passive cooling cycle. T_{initial} is varied until $T_{\text{initial}} = T_{\text{out}}$.



(b) Notional active cooling cycle. T_{initial} is varied until $T_{\text{initial}} = T_{\text{out}}$, however T_{initial} now represents the inlet to the heat pump, as opposed to the heat acquisition. In the active cooling cycle, the inlet to the heat acquisition is a return temperature, controlled by the optimizer.

Fig. 2 Notional cycles and their interaction with the temperature solver.

where mass flow index, j , represents the unique coolant loop in which component i is located. i represents the component index and $T_{i,\text{in}} = T_{i-1,\text{out}}$ only if components i and $i - 1$ exist on the same loop j . Otherwise, j is incremented and, as discussed previously, if i is the first component in loop j , then $T_{i,\text{in}} = T_{j,\text{initial}}$. ϵ_i symbolizes the component acquisition effectiveness, $\dot{Q}_i$ the component heat production, and c_{coolant} the coolant specific heat.

The partial derivatives of the final temperature(s) are required with respect to the initial temperature(s) to enable a gradient-based solve to close the thermodynamic cycle. This partial derivative is a matrix with rows n_i by columns n_j , i.e. the number of components by the number of unique cooling loops. The partial derivative of the outlet temperature of the first component in each loop with respect to the initial temperature of the loop is given in Eq. 2 as

$$\frac{\partial T_{1,\text{out}}}{\partial T_{j,\text{initial}}} = \frac{\partial}{\partial T_{j,\text{initial}}} \left(T_{j,\text{initial}} + \frac{\dot{Q}_1}{\epsilon_1 \dot{m}_j c_{\text{coolant}}} \right) = 1 \quad (2)$$

Because the inlet and outlet temperatures of all components downstream of component 1 are dependent on the outlet temperature of component 1, this partial derivative will propagate downstream to all components on the same coolant loop j .

The partial derivatives of the temperatures with respect to the mass flows and heat loads will be required as the optimizer will directly control mass flow and indirectly control heat loads through sizing of heat producing components. The partial of the temperatures with respect to the mass flows is a matrix with rows n_i by columns n_j , similar to that with respect to the initial temperatures. This partial derivative is given in Eq. 3 as

$$\frac{\partial T_{i,\text{out}}}{\partial \dot{m}_j} = \frac{\partial T_{i,\text{in}}}{\partial \dot{m}_j} - \frac{\dot{Q}_i}{\epsilon_i \dot{m}_j^2 c_{\text{coolant}}} \quad (3)$$

where $\frac{\partial T_{i,\text{in}}}{\partial \dot{m}_j} = \frac{\partial T_{i-1,\text{out}}}{\partial \dot{m}_j}$, and is propagated from upstream. This also assumes components i and $i - 1$ are on the same mass flow loop j . The partial of the temperatures with respect to the component heat loads is a matrix with rows n_i by

columns n_i . This partial derivative is given in Eq 4 as

$$\frac{\partial T_{i,\text{out}}}{\partial \dot{Q}_i} = \frac{1}{\epsilon_i \dot{m}_j c_{\text{coolant}}} \quad (4)$$

Gradient propagation for heat loads is unique but still present. To complete the Jacobian matrix, the off-diagonal terms of $\frac{\partial T_{\text{out}}}{\partial \dot{Q}}$, not given in Eq. 4, are required. Outlet temperature i will propagate its partial derivative with respect to heat load i to all outlet temperatures which are downstream. For example, if components 1, 2, and 3 are in series, row 3 of $\frac{\partial T_{\text{out}}}{\partial \dot{Q}}$ will have a nonzero entry not only in column 3, but in columns 1 and 2 as well.

2. Evaluation and Gradients of Heat Pump Components

The heat pumps in this work are modeled as modified coolant cycles, whereby a prescribed “return” temperature is set by the optimizer as the initial temperature for the heat acquisition loop. The heat rejection loop then collects the heat acquired as well as the additional heat removed to reach the desired return temperature. This heat raises the temperature of the coolant in the rejection loop. Since the initial temperature of the acquisition loop is now known, but the initial temperature of the rejection loop is not, the solver will instead find this new unknown. Figure 2 illustrates this difference between architectures with and without heat pumps. The rejection loop assumes a reduction in coolant mass to approximate replacement of liquid coolant with a two-phase vapor refrigerant. Future work will expand upon this simplified methodology with a model of a refrigeration cycle.

The inclusion of a heat pump component necessitates the addition of an additional mass flow loop and an additional partial derivative: that of the outlet temperatures with respect to the return temperature. Heat producing component derivatives described in Eq. 2 are now equal to zero, while the partial derivatives with respect to the return temperatures, previously nonexistent, are given in Eq. 5 as

$$\frac{\partial T_{1,\text{out}}}{\partial T_{j,\text{return}}} = \frac{\partial}{\partial T_{j,\text{return}}} \left(T_{j,\text{return}} + \frac{\dot{Q}_1}{\epsilon_1 \dot{m}_j c_{\text{coolant}}} \right) = 1 \quad (5)$$

The temperature rise across the heat pump is given in Eq. 6

$$T_{i,\text{out}} = T_{j,\text{initial}} + \frac{\dot{m}_{j-1} c_{\text{coolant}} (T_{i-1,\text{out}} - T_{j-1,\text{return}})}{\dot{m}_j c_{\text{refrigerant}}} \quad (6)$$

where $j - 1$ represents the heat acquisition loop which is upstream of this heat pump component and j represents the heat rejection loop. $T_{i-1,\text{out}}$ is the temperature immediately preceding the heat pump on the heat acquisition loop, however in this case it is not equal to $T_{i,\text{in}}$, as $T_{i,\text{in}} = T_{j,\text{initial}}$. The partial derivative $\frac{\partial T_{i,\text{out}}}{\partial T_{j,\text{initial}}}$ is equal to 1, similar to any heat producing component, and it will propagate this sensitivity downstream to any heat sink the rejection loop uses. It is essential to preserve the partial derivatives of this component’s outlet temperature with respect to upstream heat loads and mass flows, which are implicit in $T_{i-1,\text{out}}$. The partial derivative of the heat pump outlet temperature with respect to mass flows is given in Eqs. 7 and 8 as

$$\frac{\partial T_{i,\text{out}}}{\partial \dot{m}_{j-1}} = \frac{c_{\text{coolant}}}{\dot{m}_j c_{\text{refrigerant}}} \left(T_{i-1,\text{out}} + \dot{m}_{j-1} \frac{\partial T_{i-1,\text{out}}}{\partial \dot{m}_{j-1}} - T_{j-1,\text{return}} \right) \quad (7)$$

$$\frac{\partial T_{i,\text{out}}}{\partial \dot{m}_j} = - \frac{\dot{m}_{j-1} c_{\text{coolant}}}{\dot{m}_j^2 c_{\text{refrigerant}}} \left(T_{i-1,\text{out}} - T_{j-1,\text{return}} \right) \quad (8)$$

where $\frac{\partial T_{i-1,\text{out}}}{\partial \dot{m}_{j-1}}$ is taken from the upstream, where it would have been calculated during the evaluation of component $i - 1$. The partial derivative of the heat pump outlet temperature with respect to component heat loads is given in Eq. 9 as

$$\frac{\partial T_{i,\text{out}}}{\partial \dot{Q}} = \frac{\dot{m}_{j-1} c_{\text{coolant}}}{\dot{m}_j c_{\text{refrigerant}}} \times \frac{\partial T_{i-1,\text{out}}}{\partial \dot{Q}} \quad (9)$$

Note that this sensitivity must be propagated with respect to all components in the upstream heat acquisition loop. Finally, the heat pump outlet temperature is sensitive to the return temperature prescribed by the optimizer, and this partial derivative is given in Eq. 10 as

$$\frac{\partial T_{i,\text{out}}}{\partial T_{j,\text{return}}} = \frac{-\dot{m}_{j-1} c_{\text{coolant}}}{\dot{m}_j c_{\text{refrigerant}}} \quad (10)$$

3. Evaluation and Gradients of Air-Rejecting Heat Sinks

This work assumes that to reject heat to the atmosphere, an air scoop will allow the flow of cool ambient air to pass over a heat exchanger, dropping the temperature of the coolant by some amount. The temperature of the coolant after the heat exchanger is expressed in Eq. 11 as

$$T_{i,\text{out}} = T_{i,\text{in}} - \frac{\epsilon_i \dot{Q}_{\text{max}}}{\dot{m}_{\text{coolant}} c_{\text{coolant}}} \quad (11)$$

where $\dot{Q}_{\text{max}}$ is the maximum idealized heat transfer possible between the coolant and the ambient air. This quantity depends on the minimum heat capacity rate between the coolant and the air. Taking a minimum would introduce a discontinuity which cannot be differentiated. However, the assumption that the limiting factor is always the coolant can be introduced and subsequently enforced through a constraint at the optimization level. The optimization constraint is discussed in Section II.D. This assumption fixes $\dot{Q}_{\text{max}}$ as shown in Eq. 12 below

$$\dot{Q}_{\text{max}} = \dot{m}_{\text{coolant}} c_{\text{coolant}} (T_{\text{coolant}} - T_{\text{ambient}}) \quad (12)$$

substituting Eq. 12 into Eq. 11 with $T_{\text{coolant}} = T_{i,\text{in}}$ yields

$$T_{i,\text{out}} = T_{i,\text{in}} - \frac{\epsilon_i \dot{m}_{\text{coolant}} c_{\text{coolant}} (T_{i,\text{in}} - T_{\text{ambient}})}{\dot{m}_{\text{coolant}} c_{\text{coolant}}} = T_{i,\text{in}} (1 - \epsilon_i) + \epsilon_i T_{\text{ambient}} \quad (13)$$

The partial derivatives for the air heat exchanger outlet temperature are simply propagated from upstream components and are given below in Eq. 14

$$\frac{\partial T_{i,\text{out}}}{\partial (\circ)} = (1 - \epsilon_i) \frac{\partial T_{i,\text{in}}}{\partial (\circ)} = (1 - \epsilon_i) \frac{\partial T_{i-1,\text{out}}}{\partial (\circ)} \quad (14)$$

where $\circ$ represents any of the following: component heat rates $\dot{Q}$, mass flow rates $\dot{m}$, return temperatures T_{return} , or initial temperatures T_{initial} . The exception is the partial with respect to the ambient temperature, which is given in Eq. 15 as

$$\frac{\partial T_{i,\text{out}}}{\partial T_{\text{ambient}}} = \epsilon_i \quad (15)$$

because the forward temperature solve is wrapped in an iterative solver to ensure the initial and final temperatures are equal, other components' outlet temperatures do not have partial derivatives with respect to ambient temperature, and this sensitivity is captured in the iterative solver level.

4. Evaluation and Gradients of Fuel-Rejecting Heat Sinks

The outlet temperature of a fuel heat exchanger is nearly identical to that for an air heat exchanger, but is modified slightly to depend on the fuel temperature as opposed to the ambient, as shown below in Eq. 16

$$T_{i,\text{out}} = T_{i,\text{in}} (1 - \epsilon_i) + \epsilon_i T_{\text{fuel}} \quad (16)$$

the partial derivatives of the outlet temperature for a fuel heat exchanger with respect to all variables except the fuel and ambient temperatures are identical to those described in Eq. 14, and the partial derivative of the outlet temperature with respect to the fuel temperature is shown in Eq. 17 below

$$\frac{\partial T_{i,\text{out}}}{\partial T_{\text{fuel}}} = \epsilon_i \quad (17)$$

Similar to the fact that the air heat exchanger is the only component with a nonzero sensitivity to the ambient temperature, the fuel heat exchanger outlet temperature is the only component sensitive to the temperature of the fuel.

The third output in Table 1 has thus far been unaddressed, as the other components do not explicitly affect the rate at which the fuel temperature increases. This quantity is necessary for two reasons: first, the cooling capability of the fuel depends on its temperature, and second, the fuel temperature must be kept below a safe operating limit. The variable of interest is the rate of change of fuel temperature $\dot{T}_{\text{fuel}}$, and not fuel temperature itself, as mission time-steps vary between aircraft design optimizations, and state variables are usually collected at the optimization level. The rate of change of the fuel temperature is given in Eq. 18 as

$$\dot{T}_{\text{fuel}} = \frac{c_{\text{coolant}}}{m_{\text{fuel}} c_{\text{fuel}}} \sum \epsilon_i \dot{m}_i (T_{i,\text{in}} - T_{\text{fuel}}) \quad (18)$$

where the sum includes all components i which are fuel heat exchangers, and $\dot{m}_i$ is the coolant mass flow rate through component i . The partial derivative of $\dot{T}_{\text{fuel}}$ is required with respect to fuel mass as the fuel mass will be sized according to propulsive *and* thermal requirements as opposed to just propulsive in a conventional case. This is further discussed in Section II.D, and the partial derivative is given in Eq. 19 below

$$\frac{\partial \dot{T}_{\text{fuel}}}{\partial m_{\text{fuel}}} = -\frac{c_{\text{coolant}}}{m_{\text{fuel}}^2 c_{\text{fuel}}} \sum \epsilon_i \dot{m}_i (T_{i,\text{in}} - T_{\text{fuel}}) \quad (19)$$

Similar to Eq. 18, this sum includes all i that are fuel heat exchangers. The partial derivatives with respect to the remaining inputs are given in Eq. 20 through Eq. 24 below. All summations imply summing over components which are fuel heat exchangers, as several cooling loops architected in parallel can reject heat to the same sink.

$$\frac{\partial \dot{T}_{\text{fuel}}}{\partial \dot{Q}} = \frac{c_{\text{coolant}}}{m_{\text{fuel}} c_{\text{fuel}}} \sum \epsilon_i \dot{m}_i \frac{\partial T_{i,\text{in}}}{\partial \dot{Q}} \quad (20)$$

$$\frac{\partial \dot{T}_{\text{fuel}}}{\partial \dot{m}_i} = \frac{c_{\text{coolant}}}{m_{\text{fuel}} c_{\text{fuel}}} \sum \epsilon_i \left(T_{i,\text{in}} + \dot{m}_i \frac{\partial T_{i,\text{in}}}{\partial \dot{m}_i} - T_{\text{fuel}} \right) \quad (21)$$

care should be taken with the partial derivative shown in Eq. 21 as the heat exchanger inlet temperature may depend on two upstream mass flows in the case that this exchanger is downstream of a heat pump.

$$\frac{\partial \dot{T}_{\text{fuel}}}{\partial T_{\text{return}}} = \frac{c_{\text{coolant}}}{m_{\text{fuel}} c_{\text{fuel}}} \sum \epsilon_i \dot{m}_i \frac{\partial T_{i,\text{in}}}{\partial T_{\text{return}}} \quad (22)$$

$$\frac{\partial \dot{T}_{\text{fuel}}}{\partial T_{\text{initial}}} = \frac{c_{\text{coolant}}}{m_{\text{fuel}} c_{\text{fuel}}} \sum \epsilon_i \dot{m}_i \frac{\partial T_{i,\text{in}}}{\partial T_{\text{initial}}} \quad (23)$$

$$\frac{\partial \dot{T}_{\text{fuel}}}{\partial T_{\text{fuel}}} = -\frac{c_{\text{coolant}}}{m_{\text{fuel}} c_{\text{fuel}}} \sum \epsilon_i \dot{m}_i \quad (24)$$

5. Closing the Thermodynamic Cycle

Thus far, each component's outlet temperature has been detailed as a function of that component's inlet temperature. Each mass flow loop is built component-by-component with an initial coolant temperature assumed, and the final coolant temperature (outlet of the final component in each loop) is calculated after each component in the loop contributes heat addition or rejection. However, as mentioned previously, this forward solve is only a closed thermodynamic loop, and therefore a valid solution, if the initial temperature is equal to the final temperature. Because the partial derivatives of the outlet temperatures with respect to the initial temperature have been book-kept throughout the forward solve, this enforcement is somewhat trivial. A Newton solver can solve Eq. 25 for T_{initial} since $\frac{\partial T_{\text{final}}}{\partial T_{\text{initial}}}$ is known.

$$T_{\text{initial}} - T_{\text{final}}(T_{\text{initial}}, \dots) = 0 \quad (25)$$

note that T_{final} is also a function of the previously mentioned component heat loads, coolant mass flow rates, etc. However, these variables are either fallouts from the aircraft mission, such as ambient temperature, or are varied by the optimizer, such as mass flow rate. Within a given optimization iteration, these variables will not change, and the equilibrium temperature reached when $T_{\text{initial}} = T_{\text{final}}$ is unique to the combination of values taken by the other variables.

C. Subsystem Components and Key Performance Parameters

From a system-level perspective, the aircraft and its energy consumption (or similar performance metric) are only dependent on three impacts of a TMS: the drag, weight, and power consumption. The methodology uses a variety of models for the various components which make up the TMS to quantify these system level impacts. Most models are functions of variables known as ‘‘Key Performance Parameters’’ or KPPs. Systems level studies often use KPPs as alternatives to complex models, which at the cost of higher fidelity, provide several advantages. KPPs often represent a subsystem-level performance metric, useful for defining required technological progress for system level feasibility. For

example, a KPP for a fully electric aircraft is battery specific energy. While this parameter does not fully capture the complex dynamics that a high fidelity battery model could provide, it is useful in defining limits for pack-level energy requirements. Additionally, varying KPP values to quantify a system level performance metric (energy consumption) sensitivity helps to highlight subsystems which contribute the most to vehicle performance. Using KPP models for low-impact subsystems can reduce the number of required design variables in an optimization problem, increasing robustness and decreasing computation time. Lastly, KPPs can often be calculated from values in existing databases, making it easy to choose realistic values for design studies, or to predict a value in the near future.

The KPP-driven approach for aircraft systems design has been established in previous literature. Jansen et al. [23, 24], Duffy and Jansen [25], and Acar et al. [26] establish the utility in KPPs for conceptual aircraft design, while Stalcup et al. [18] specifically define KPPs for thermal management systems in electrified aircraft. The thermal management system KPPs established in Stalcup et al. [18] are adapted for use in this work, as detailed in Table 2.

Heat Producers: propulsive elements such as motors, generators, batteries, and power converters will all produce waste heat which needs to be carried away to avoid overheating. Each of these components is modeled at several levels of fidelity in the overarching aircraft design framework described in Kaneko et al. [20], and has a corresponding heat production model. In the absence of a higher fidelity model, the heat production falls back onto a simple relation, shown in Eq. 26.

$$\dot{Q}_i = (1 - \eta_i) \times P_i \quad (26)$$

where $\dot{Q}_i$ is a component heat production, η_i is the component's efficiency, and P_i is the power produced by the component.

Fluid Pumps: each coolant loop requires a pump to circulate coolant between TMS components. Consequently, each fluid pump contributes to the weight and power offtake of the TMS. The power offtake per pump is shown in Eq. 27

$$P_{\text{pump}} = \frac{\dot{m}gh_f}{\eta_{\text{pump}}} \quad (27)$$

where P_{pump} is the required fluid pump power, $\dot{m}$ is the coolant mass flow rate required by the TMS, g is the gravitational constant, h_f is the total head loss of the system, and η_{pump} is the pump efficiency. The system head loss is modeled as a linear function of the total length of pipe which this pump provides coolant flow for. The relation is given in Eq. 28 below

$$h_f = h_l l \quad (28)$$

where h_l is a unitless quantity representing the head loss per unit length of pipe and l is the pipe length. The pump weight is sized by its requisite mass flow rate and is given in Eq. 29 below

$$W_{\text{pump}} = w_m \dot{m}_{\text{coolant}} \quad (29)$$

where w_m is in units of $kg/(kg/s)$, or simply s . $\dot{m}_{\text{coolant}}$ is the maximum coolant mass flow rate that is required by this pump, in units of kg/s .

Heat Pumps: an architectural option is to use a heat pump, which consumes power to drive a temperature difference between two separate fluid loops. The heat pump system will require a weight and power consumption model. To calculate the power required, an assumed (cooling) coefficient of performance is used, as shown in Eq. 30.

$$P_{\text{HP}} = \frac{\dot{Q}_c}{COP_c} \quad (30)$$

where P_{HP} is the heat pump power, $\dot{Q}_c$ is the heat transfer required to lower the temperature of the component-pump coolant to the colder return temperature (design variable), and COP_c is the cooling coefficient of performance. Similar to the fluid pump, an assumed specific power is used as a preliminary weight estimation method.

Plumbing: coolant needs to be transported between sources, exchangers, and sinks. TMS piping is assumed to be annular in shape, and the weight is given in Eq. 31 as

$$W = 1.2 \times \pi((r_i + t)^2 - r_i^2) \times l \times \rho_{\text{pipe}} \quad (31)$$

where r_i is the inner pipe radius, t is the pipe thickness, l is the tube length, ρ_{pipe} is the material density, and the factor of 1.2 is applied to account for fittings, clamps, valves, etc. Byahut and Uranga [13] originally applied this factor for electrical wiring weights, however it is adapted here for plumbing fixtures. r_i is calculated according to

$$r_i = \sqrt{\frac{\dot{m}}{\rho_{\text{coolant}} u \pi}} \quad (32)$$

where $u = 8$ ft/s is an assumed average coolant flow velocity at the sizing condition, and ρ_{coolant} is set by a user according to the choice of coolant. t is a function of r_i , determined by a linear fit to steel piping schedules which are set by the American Society of Mechanical Engineers and the American National Standards Institute. Schedules increase in thickness and range from Schedule 5 to Schedule 160, with extra thick variants available above 160, although Schedule 40 is the “standard” thickness. Data for the linear fit was sourced from the Engineering Toolbox [27], a free online resource for common engineering data. The linear fit is shown in Fig. 3 and has a coefficient of determination $R^2 = 0.9875$ with a root mean squared error of 0.52 millimeters. The exact relation is given in Eq. 33, where both thickness and inner pipe radius are assumed to be in millimeters. Although steel piping sizes were used, this work assumes that aluminum would be used in an aeronautical application, thus $\rho_{\text{pipe}} = 2,700$ kg/m³.

$$t = 0.0528r_i + 2.663 \quad (33)$$

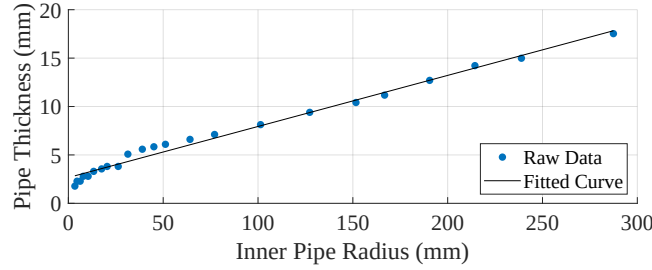


Fig. 3 Schedule 40 steel pipe thickness as a function of inner radius.

Heat Exchangers: heat will need to be transferred from sources to coolant and from coolant to sink using a heat exchanger. The heat exchangers require a weight model regardless of whether they reject heat to the fuel or the air, but the air heat exchangers also require a drag model. Heat exchanger weights are parameterized by a specific power as shown in Eq. 34 below

$$W_{\text{HX}} = w \times Q \quad (34)$$

where W_{HX} is heat exchanger weight, w is weight-per-unit-heat dissipated, and Q is heat that the exchanger must transfer to the sink. The drag model is more involved than a linear scaling as it captures the effects of aircraft velocity and air duct sizes. The drag produced is modeled as a momentum loss in the air through the heat exchanger duct, parameterized by a velocity recovery factor, as shown below

$$D_{\text{HX}} = \dot{m}_{\text{air}}(u_{\infty, \text{air}} - u_{e, \text{air}}) \quad (35)$$

where

$$u_{e, \text{air}} = \eta_{\text{duct}} u_{\infty, \text{air}} \quad (36)$$

this model assumes both constant air density and a constant area duct. Drag is reported as a positive quantity. The area of the duct, which is an optimization design variable, is discussed in Section II.D.

Table 2 summarizes the KPPs which parameterize the TMS performance outlined in this work. In addition to the KPPs introduced by the TMS component models, the temperature limits of the electrical components also affect the size and subsequent impact of a TMS onboard an aircraft. Lower temperature limits require a more demanding cooling system, which is therefore heavier and more power-consuming.

Table 2 Key performance parameters and their sources for the thermal management system described in this work.

KPP	Source
Propulsion Component Efficiency	Stalcup et al. [18]
Heat Acquisition and Rejection Effectiveness	Stalcup et al. [18]
Coolant Pipe Length	Original
Fluid Head Loss per Pipe Length	Original
Fluid Pump Specific Weight	Original
Heat Pump Specific Weight	Stalcup et al. [18]
Heat Pump Coefficient of Performance	Stalcup et al. [18]
Pipe Thickness (Schedule)	Original
Heat Exchanger Specific Weight	Stalcup et al. [18]
Air Duct (Scoop) Efficiency	Original
Propulsion Component Temperature Limits	Stalcup et al. [18]

D. Integration into an Optimization Framework

With the temperature of the coolant and refrigerant between each component in the TMS determined by the temperature solver, and the weight, power, and drag impacts of each component determined through the KPP relations, the thermal management subsystem can be integrated into the vehicle level optimization. Currently, this work exists as an extension of NASA’s Aviary [28], a python-based aircraft optimization framework built atop Dymos [29] and OpenMDAO [30], although the methodology established could be integrated into any optimization or modeling framework. Regardless, to quantify the system level impacts, the TMS needs to be properly sized for its application while avoiding violation of any constraints established by the designer or the assumptions made during the modeling process. This is carried out by the optimizer through control of design variables. This section will outline the design variables and their associated constraints introduced by the TMS model.

Coolant and Refrigerant Mass Flow Rate: Coolant and refrigerant mass flow rates determine the equilibrium temperature to which the temperature solver converges. To ensure that this equilibrium temperature falls within acceptable limits, the optimizer requires control over these mass flow rates. Additionally, the weight of the fluid pumps depend on the maximum mass flow through each pump. The optimizer controls both the maximum possible mass flow in each loop as well as the mass flow at each time step in the aircraft’s mission. There are two constraints associated with this design variable. First, the optimizer must ensure that the temperature at the outlet of each component is less than or equal to that component’s maximum allowable temperature. Second, the mass flow at any arbitrary point must be less than or equal to the maximum mass flow. This constraint ensures that the system can never use more coolant than it is sized for. If more coolant is required, the maximum flow must increase and therefore the weight of the pumps and plumbing as well.

Air Duct Area: The optimizer is given control over the size of the ducts which provide air to the air-cooled heat exchangers. The temperature solver assumes that an air heat exchanger can always provide more cooling capacity than that of the coolant or refrigerant in the TMS. This assumption is necessary to avoid a discontinuity in the forward solve, ensuring differentiability. It is enforced by a constraint that $\dot{m}_{\text{air}} c_{\text{air}} \geq \dot{m}_{\text{coolant}} c_{\text{coolant}}$ at all points in the mission. Since the air mass flow is a direct function of the duct area, the optimizer will ensure that the duct is always sufficiently large to provide this cooling capability. Arbitrarily large air ducts are punished by drag penalties, which harm aircraft level objective functions such as energy consumption. It is worth noting that enforcing the air to have a higher cooling capacity means that the air ducts are always sized such that at any point in the mission which is not the sizing condition, the TMS will throttle back the coolant flow. This would prevent the optimizer from trading off between air duct size and maximum coolant flow only if the maximum mass flow *was not* a design variable. Because it is, the optimizer is able to choose between having a large coolant flow with a small air duct or a large air duct with a small coolant flow depending on the impact of drag and plumbing weight at the system level. This relationship is explored further in Section IV.

Fuel Mass (Ballast): If an architecture uses fuel as a heat sink, the optimizer requires the ability to add additional

fuel to the tanks as a thermal ballast. For example, towards the end of a mission, the fuel levels in the vehicle may be sufficiently low that the cooling capacity is unable to dissipate any heat from the TMS. Therefore, additional fuel may be added to increase this cooling capacity. The clear drawback is the addition of extra weight. The temperature of the fuel must be constrained at all mission points to stay below a safe operating limit, assumed to be 38°C. Enforcing this temperature limit implicitly enforces the assumption that the cooling capacity of the fuel is greater than that of the coolant, as a violation of this assumption would result in component overheating, a constraint which is already enforced.

Heat Pump Return Temperature: In architectures which utilize heat pumps, the return temperature, that is, the temperature to which the heat pumps drop the coolant, is a design variable. It is constrained such that the power required to perform this drop must be less than or equal to the power for which the heat pump was sized.

III. Comparison to Literature

There are several studies which report figures that enable a subsystem level comparison to the methodology presented in this work. While these studies vary between aircraft classes, mission profiles, and TMS architectures, their mass-specific heat rejection capabilities at various gross heat productions can provide a range of subsystem performance metric comparison points. The STARC-ABL concept described in Welstead and Felder [2] assumes a specific heat rejection of 0.68 kW/kg for a partially turboelectric single-aisle airliner. The STARC-ABL TMS was not modeled in detail. The Eco-150R, a fully turboelectric single-aisle from Schiltgen and Freeman [31], estimates a specific heat rejection of 1.802 kW/kg, cooled through a liquid-air heat exchanger. Byahut and Uranga [13] designed a fully electric commuter based on the Viking Air Twin-Otter, which varied in its specific heat rejection depending on the number of distributed propulsors used. Assuming two propulsors, the specific heat rejection was 0.617 kW/kg, as opposed to 0.567 kW/kg in a 20 propulsor configuration. This concept was cooled using a counterflow liquid-air heat exchanger. The SUSAN concept, a partially turboelectric single-aisle concept with distributed underwing propulsors, had a detailed TMS modeled in the work of Stalcup et al. [18]. Specific heat rejections ranged between 0.153 and 0.171 kW/kg depending on assumptions in component technology levels. SUSAN's TMS is complex, consisting of many cooling loops with both passive and active (i.e. two-phase refrigeration cycles). Shekar and Clarke [14] also designed a fully electric Twin-Otter, but the cooling system consisted of large coolant reservoirs passively cooled through the skin of the wings as opposed to a conventional heat exchanger. These concepts are summarized in Table 3.

A subsystem parameter sweep is designed to capture the wide range of propulsive and thermal architectures, subsystem technology assumptions, and aircraft size classes that these aircraft assume or belong to. This sweep is performed using a simple thermal architecture consisting of a single heat-producing component and a single liquid-air heat exchanger. While this simplification will not faithfully recreate any of the architectures described in the literature, it will allow the parameter sweep to generally capture the impact of subsystem performance metrics on the specific heat rejection. The parameter sweep shows this relationship as a function of the heat load the system must accommodate. It varies depending on the temperature limit of the heat producer, the assumed plumbing length, whether the TMS is sized for top of climb (TOC) or takeoff (TKO) conditions, and assumed subsystem technology level. Tables 4 and 5 define flight conditions and technology levels explicitly. Figure 4 shows the specific heat rejection curves for each combination of pipe length, component temperature limit, technology level, and flight condition. Longer pipe lengths require more tubing and more coolant to fill the tubes, leading to an intuitive decrease in specific heat rejection as pipe length increases. Higher temperature limits allow the TMS to reject heat to the ambient atmosphere at a larger temperature difference between coolant and air, which reduces the required coolant mass and subsequent TMS mass, leading to an increase in performance as temperature limits relax. Intuitively, higher technology levels increase the specific heat rejection as they increase component performance. It is not straightforward to directly compare takeoff and top of climb because when they are integrated into the aircraft system, heat loads will not be equivalent at these conditions. However, when these heat loads are assumed equal, the TMSs sized for takeoff outperform those sized for top of climb at low power. The lower temperature at top of climb combined with the higher flight speed benefits the TMS despite the lower air density, however the specific heat rejection increase is limited by a lower limit on piping diameter, which may restrict flow if it becomes too small (as is the case for low heat loads). The limit for this parameter sweep was arbitrarily set at 2.5 millimeters. Once the TMS would require a pipe diameter larger than 2.5 millimeters, the top of climb sizing condition becomes favorable. This generally occurs around a heat load of 10 kW. Additionally, the air ducts were limited to six meters in diameter, which does not allow sufficient air to cool the system at any heat load at the takeoff condition, since the ambient temperature is equal to the limit. In practice, cooling a system with

Table 3 Aircraft concepts from literature, their propulsive and thermal architectures, and their subsystem-level performance metrics.

Concept	Class	Propulsion Architecture	TMS Architecture	Heat Rejection (kW)	TMS Weight (kg)	Specific Heat Rejection (kW/kg)
STARC-ABL	Single-aisle	Partially Turboelectric	Not Modeled	279	410	0.680
ECO-150R	Single-aisle	Fully Turboelectric	Liquid-Air HEX	1491	827	1.802
Byahut 2	Commuter	All Electric	Liquid-Air HEX	63	102	0.617
Byahut 20	Commuter	All Electric Distributed	Liquid-Air HEX	70	123	0.567
SUSAN (TRL 5+)	Single-aisle	Partially Turboelectric Distributed	Combined Liquid-Air Two-Phase	45	264	0.171
SUSAN (TRL 3-4)	Single-aisle	Partially Turboelectric Distributed	Combined Liquid-Air Two-Phase	90	528	0.171
SUSAN (TRL 1-2)	Single-aisle	Partially Turboelectric Distributed	Combined Liquid-Air Two-Phase	195	1273	0.153
Shekar Config-1	Commuter	All Electric	Liquid-Air Skin	2.92	230	0.0127
Shekar Config-2	Commuter	All Electric	Liquid-Air Skin	2.25	375	0.0060
Shekar Config-3	Commuter	All Electric	Liquid-Air Skin	2.04	275	0.0074

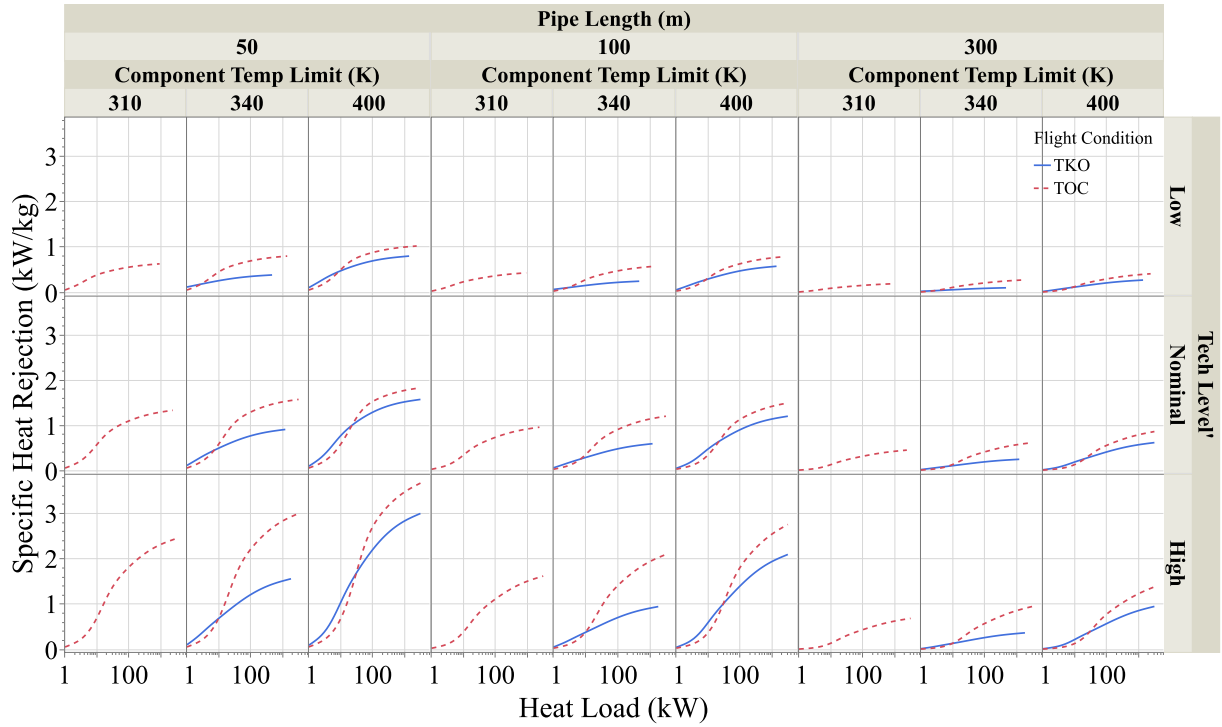


Fig. 4 Specific heat rejection vs heat load for a variety of subsystem assumptions. Note that the heat load axis is log scaled.

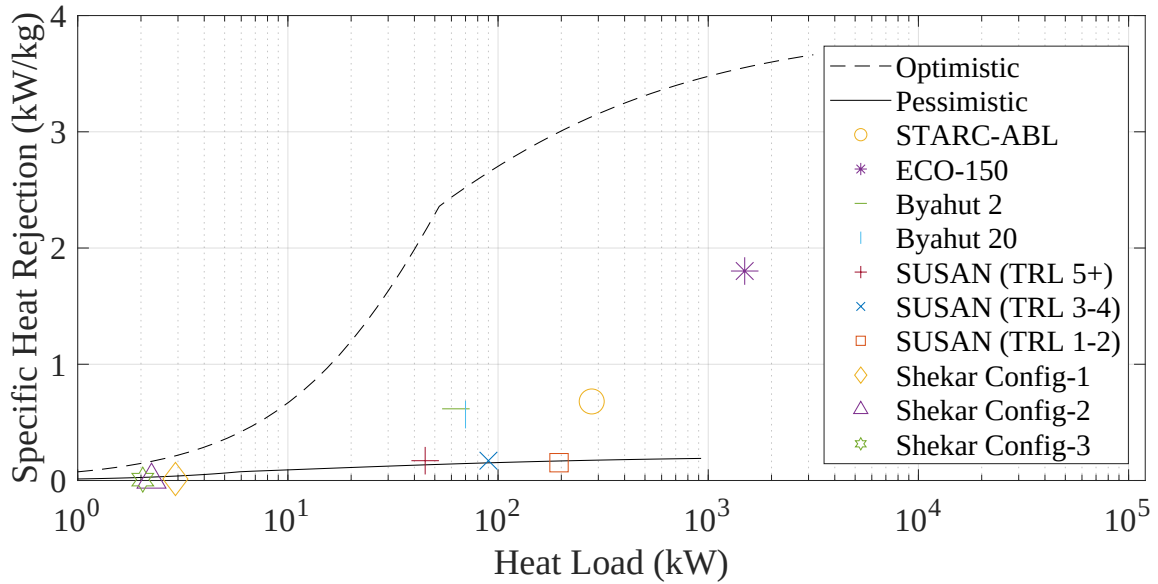


Fig. 5 Literature specific heat rejections alongside optimistic (high technology level, short pipe length, high temperature limit) and pessimistic (high technology level, long pipe lengths, low temperature limit) curves at the top of climb sizing condition.

Table 4 Flight conditions for assumed sizing point of the simple TMS.

Flight Condition	Freestream Velocity (m/s)	Freestream Air Density (kg/m ³)	Freestream Temperature (K)
Takeoff (TKO)	30	1.23	310
Top of Climb (TOC)	250	0.4	250

Table 5 Subsystem performance parameter values for various technology levels in the simple TMS parameter sweep. All acquisition effectivenesses are equal to ensure that every level sees the same equivalent heat load.

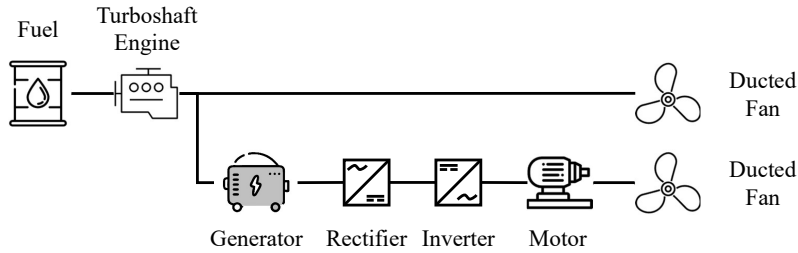
Technology Level	Coolant Specific Weight (kg/kg/s)	Pump Weight	Liquid-Air HEX Specific Weight (kg/kW)	Liquid-Air HEX Effectiveness	Heat Acquisition Effectiveness
Low	12		0.5	0.2	0.5
Nominal	6		0.35	0.5	0.5
High	4		0.15	0.7	0.5

demanding temperature limits and high ambient temperatures would require a refrigeration cycle.

Figure 5 shows the literature values alongside optimistic and pessimistic curves, representing favorable and unfavorable values for the parameters from the sweep. This figure illustrates that the methodology in this paper is capable of capturing a wide range of relationships between subsystem demand and performance, and is comparable to existing literature.

IV. System-Level Impacts of Thermal Management

The TMS impact at the system level is dependent on assumed KPP values. To quantify this impact and to identify its sensitivity to the KPPs, a testbed aircraft is created for various trade and case studies. This aircraft is a notional single-aisle, partially turboelectric vehicle with a simplified propulsive power-train, as shown in Fig. 6. The testbed's design mission is a 2,500 nautical mile flight carrying a payload of 29,800 lbs, which is relaxed relative to a typical single-aisle requirement. This relaxation encourages optimizer convergence for designs in the trade studies which assume conservative values for all KPPs.

**Fig. 6** Propulsion architecture for the notional single-aisle testbed: a partially turboelectric powertrain with a single mechanical and a single electric propulsor.

The turboshaft engine's fuel consumption is modeled using an engine-deck, created in PyCycle [32]. The engine deck is a multidimensional lookup table where fuel consumption and output power are reported as functions of altitude, flight speed, and throttle. Each point is generated in advance through an off-design engine evaluation in PyCycle. Throughout the mission, the throttle is varied to achieve the power output required by the propulsion system to maintain the aircraft's prescribed trajectory. Finally, a scale factor for the deck is applied to the power and fuel consumption values

from the deck to preserve the trends while varying the gross size of the engine. This work uses a turboshaft engine deck which approximates the core of a CFM-56 engine, an appropriate option for the single-aisle class. Appendix A further details the design mission and the other subsystems which are used to model the testbed aircraft.

The studies in this work compare optimized vehicles, whereby an aircraft is designed according to an optimization problem which minimizes some objective by varying design variable values, subject to a series of constraints. Section II.D details the design variables and constraints added to the optimization problem by the TMS specifically, however the system-level aircraft design optimization includes additional design variables and constraints. The objective for the vehicle design optimizations in this work is the total fuel requirement (by weight) to fly the design mission. Table 6 provides the definition for the optimizations discussed in this work.

Table 6 Top level aircraft requirements and KPPs for a notional single-aisle testbed.

		Applicable to:
minimize	fuel weight	
with respect to	engine scale factor	turboshaft engine deck
	throttle	turboshaft engine
	P_{maximum}	generator and motor
	$\dot{m}_{\text{max,coolant}}$	all coolant loops
	air duct area	air-cooled coolant loops
	extra fuel weight	
	T_{return}	all heat pumps
subject to	$P_{\text{maximum}} - P_{\text{required}}(t) > 0$	all propulsive components, all heat pumps
	$\dot{m}_{\text{max,coolant}} - \dot{m}_{\text{coolant}}(t) > 0$	all coolant loops
	$T_{\text{maximum}} - T(t) > 0$	all heat producing components, fuel
	$\dot{m}_{\text{air}}c_{\text{air}} - \dot{m}_{\text{coolant}}c_{\text{coolant}} > 0$	air-cooled coolant loops

A. Parameter Sweep Trade Studies

This trade study focuses on the effects of varying KPPs and TMS architecture to cool the notional single-aisle testbed vehicle. TMS architectures are unique to specific propulsive architectures as they are dependent on which propulsive components require cooling. Because the architecture matrices are not continuous variables and cannot be continuously relaxed, the study is repeated for two architectures. The simplified propulsion architecture used in the testbed is advantageous in this instance because representative centralized and decentralized thermal architectures can be easily defined as shown in Figs. 7a and 7b. Both of these TMS architectures assume that the generator, rectifier, inverter, and motor are power components which require coolant to remain within operational limits. The centralized architecture cools all heat producing components in series (single coolant loop) while the decentralized architecture cools each component individually (four coolant loops).

Repeated aircraft design optimizations are performed, each with a unique set of assumed values for the KPPs. This establishes the limits of the TMS effects at the system level for each architecture. The trade space is created using the Latin Hypercube sampling (LHS) method, which is a space-filling sampling technique designed to capture unique combinations of KPPs. The LHS requires upper and lower bounds to be established for each KPP, and it requires that each of them is a continuous variable (the reason varying TMS architecture requires repeated studies).

The effect of varying temperature limits is not addressed in this study, rather, it is isolated in a case study discussed in Section IV.B. Additionally, load electrification factor λ_L , is introduced. This variable governs the thrust allocation between the turboshaft-driven fan and the electric motor-driven fan. It allows the propulsion architecture to be continuously relaxed from an all conventional configuration at $\lambda_L = 0$ to an entirely turboelectric configuration at $\lambda_L = 1$. Because waste heat scales with both λ_L and propulsion component efficiency η_i , the trade space is simplified by removing component efficiencies from the parameter sweep. Generator, rectifier, inverter, and motor efficiencies are set to a nominal value of $\eta_i = 0.95$, which avoids confounding the effects of λ_L and η_i . Pipe lengths are varied continuously to simulate different strategies for component placement within an aircraft. By sweeping values for the assumed lengths, effects of plumbing redundancy and layout can be captured in a continuous manner. In a given sample

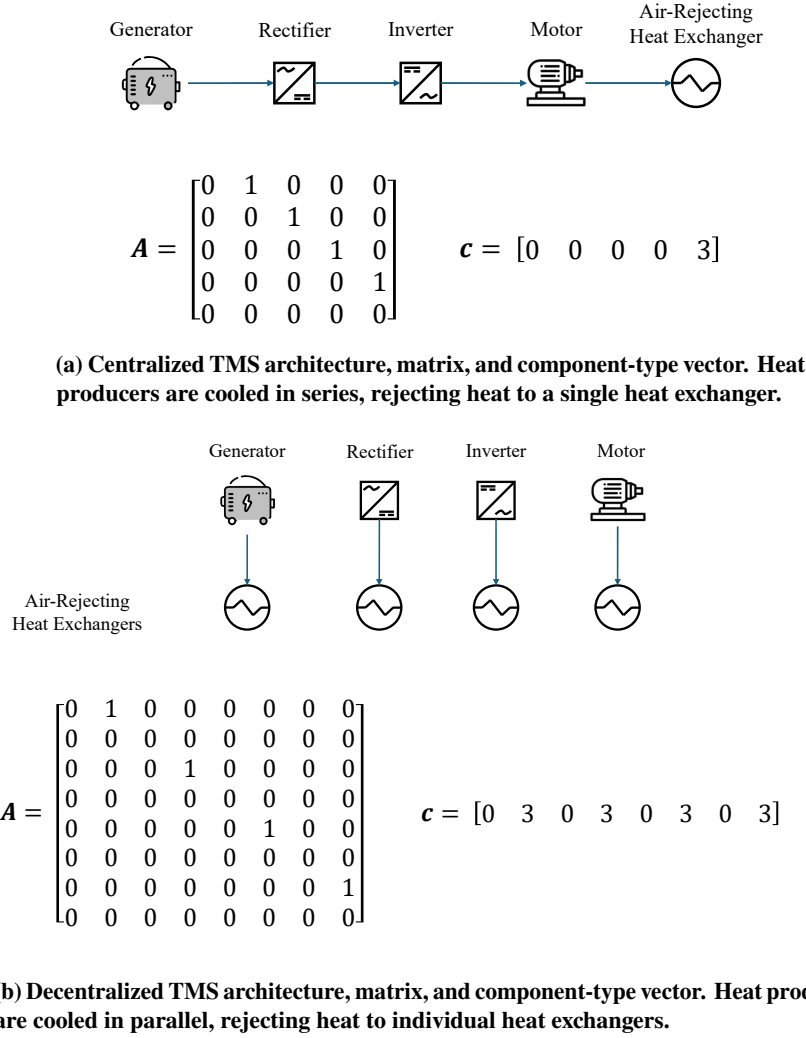


Fig. 7 TMS architectures evaluated in the air-heat exchanger parameter sweep.

of KPP values, the total length is equal between the centralized and decentralized architectures. For example, a pipe length of 40 m represents a single 40 m centralized coolant pipe and a collection of four 10 m decentralized coolant pipes. The TMS trade space is detailed in Table 7, with parameters held at their nominal values if specified.

Each architecture is optimized under 1,500 identical sets of samples using the IPOPT optimizer in pyOptSparse [33]. Each optimization is limited to 50 optimization iterations to ensure efficient use of time. Of these optimizations, some fail for a number of reasons, including infeasibility, inability to close the design (weight spiral), or failure to converge within the maximum number of iterations. The centralized architecture produced 1,224 optimized designs while the decentralized architecture produced 1,269. The success rates are 81.6% and 84.6% for centralized and decentralized architectures, respectively, implying a slight edge in robustness for the decentralized architecture, more generally, showing that the system feasibility region is affected by the subsystem architecture.

Each case is characterized by the optimized aircraft's maximum takeoff weight (MTOW), block fuel weight, and TMS weight. Comparing subsystem and system level weights, as shown in Fig. 8, for the notional partially turboelectric single-aisle testbed, the air-cooled architectures considered here, and the sampled KPP bounds, the decentralized architecture yielded lower optimized TMS weight and lower block fuel than the comparable centralized architecture over the converged cases. As both architectures are sized to dissipate the same amount of waste heat in each case, the architecture which has a smaller impact on system level block fuel is preferable. Figure 8 shows TMS weights reaching

Table 7 Parameter bounds and nominal values for the various trade and case studies.

Parameter	Lower Bound	Upper Bound	Nominal Value
Coolant Specific Heat	3.5 kJ/(kgK)	4.2 kJ/(kgK)	4.0 kJ/(kgK)
Piping Head Loss	0.3 m/m	0.7 m/m	0.5 m/m
Fluid Pump Efficiency	0.7	0.9	0.8
Fluid Pump Specific Weight	3.0 kg/(kg/s)	10.0 kg/(kg/s)	6.0 kg/(kg/s)
Air Scoop Efficiency	0.6	0.9	0.8
Air Heat Exchanger Specific Weight	0.03 kg/kW	0.3 kg/kW	0.15 kg/kW
Load Electrification Factor	0.05	0.95	0.5
Ground Air Temperature	-10 °C	40 °C	17 °C
Total Pipe Length	1 m	150 m	75 m
Electric Fan Efficiency	0.7	0.9	0.8
Heat Acquisition and Rejection Effectiveness	0.3	0.7	0.6
Component Temperature Limit	N/A	N/A	70°C

as high as 6,000 kg, while the decentralized architecture has a maximum of about 2,500 kg. The centralized architecture weights appear more sensitive to the KPPs, as the variance in TMS weight for the optimized designs is much larger than that of the decentralized architecture. The centralized architecture has a disadvantage as the entire system must be scaled to keep the last component in line, the motor, from overheating. In other words, the coolant being used to cool the motor in the centralized architecture is warmer than it would be in the decentralized architecture, leading to a relative increase in required coolant mass flow rate. As mass flow rate sizes the weight of the coolant itself, as well as the pipes and their thickness, larger required mass flow rates strongly influence the TMS weight.

TMS weight is affected by the KPPs at varying levels of sensitivity. To quantify them, a surrogate model for TMS weight is fit as a function of first and second order KPPs as well as their first order mixed terms. In other words, two terms are added to the predictor for each KPP, as well as each first order interaction between them. With 12 total inputs (architecture and 11 KPPs), this results in 89 terms in the surrogate model. This surrogate has a coefficient of determination $R^2 = 0.9278$, which indicates a strong goodness of fit. The adjusted $R^2 = 0.9251$ is very similar to the unadjusted, indicating that each term in the surrogate is contributing meaningfully to the predictor. However, in an effort to reduce the model complexity, the terms can be further reduced to just 11 while preserving a high coefficient of determination of $R^2 = 0.9110$, with an adjusted $R^2 = 0.9106$. These terms are listed in Table 8 in order of logworth*.

Logworth is calculated according to Eq. 37

$$\text{Logworth} = -\log_{10}(p) \quad (37)$$

where p is the parameter's p-value.

As seen in Table 8, the parameters have extremely high logworths, which is consistent with the fact that the data for the surrogate was produced using a deterministic, physics based model. In this instance, logworth is used as a screening technique to categorize the relative impact of the inputs on the performance metric. It is perhaps intuitive that minimizing plumbing lengths, maximizing heat acquisition and rejection effectiveness, maximizing electric fan efficiency, and choosing an appropriate TMS architecture influence the subsystem weight and therefore system level performance. However, the same is not true of load electrification factor. This parameter's effect on the TMS weight changes drastically as electrification becomes more or less desirable. To illustrate this point, Fig. 9 shows the effects of varying load electrification factor under different assumptions for load electrification factor. System level trends such as MTOW and block fuel weight are evaluated using a surrogate model generated in a manner similar to the surrogate on TMS weight discussed previously. The results were generated using the full 89 term surrogates and have coefficients of determination of $R^2_{\text{MTOW}} = 0.8856$ and $R^2_{\text{fuel}} = 0.9112$. The trends show that as electric propulsion becomes increasingly efficient, using a higher electrification factor is increasingly beneficial at the system level despite

*Logworth is a metric which transforms a parameter's p-value, the probability of obtaining results from the model which are at least as extreme as the observed model results, under the assumption that the model does not fit the observed data. More intuitively, it is the probability that a given modeling parameter was random in its contribution to the predictor. Generally, p-values below 0.05 to 0.01 are considered to indicate statistical significance.

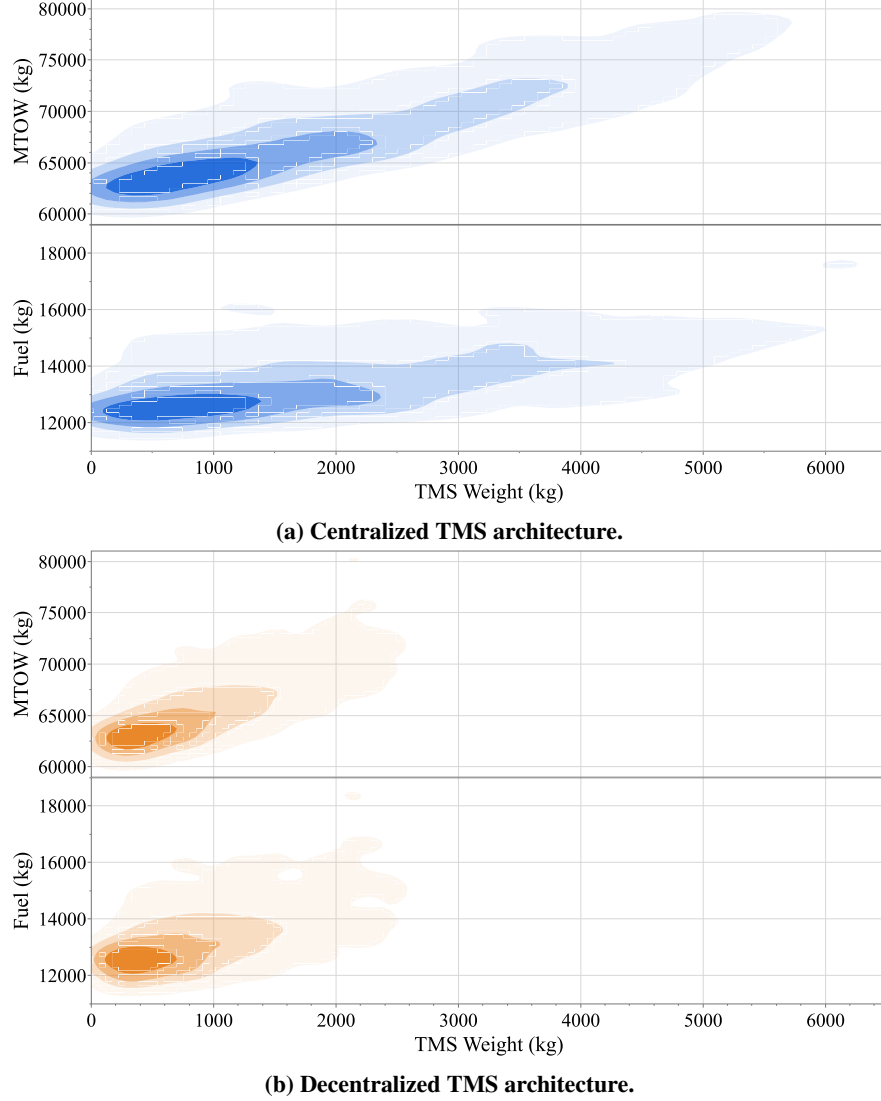
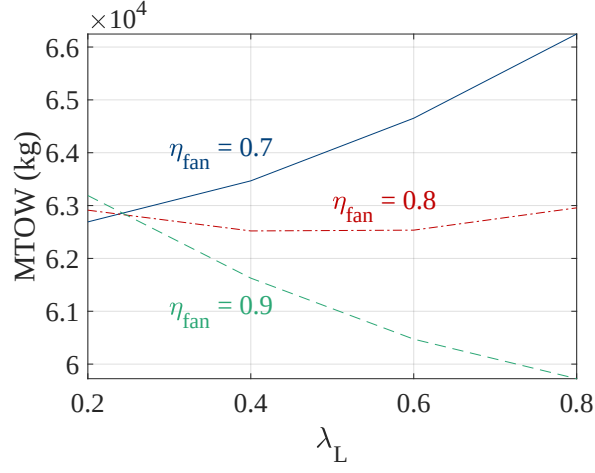


Fig. 8 MTOW and block fuel vs TMS weight, shown as density maps for converged optimization cases.

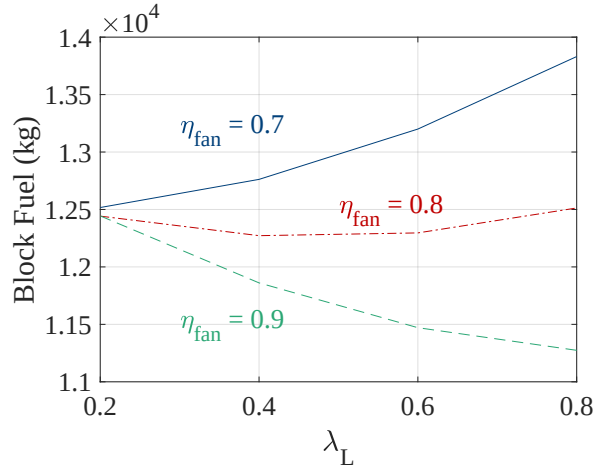
the fact that it demands a TMS which is required to dissipate more electric power. Additionally, towards the upper limits of efficiency, TMS weight begins to decrease as the load electrification factor becomes high enough, which shows that further electrifying an efficient system can relax the subsystem requirements sufficient to downsize. Figure 9 shows that there exist combinations of KPPs where load electrification factor can take a value which is optimal from the system-level perspective. Interestingly, this optimum value can exist between 0 and 1, meaning that the level of electrification on the best performing hybrid aircraft is dependent on a coupled interaction between propulsion and thermal management for the electrified powertrain.

B. Case Study: Temperature Limits

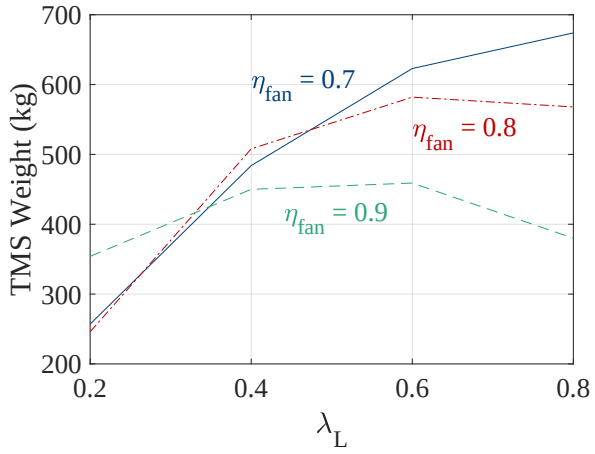
The assumption that all electrical components must be kept below the same temperature limit is inherently disadvantageous to the centralized architecture. As discussed in Section IV.A, the coolant at the outlet of the most limiting component in the series will always leave at this components maximum temperature to avoid over-sizing. If all components have the same temperature limit, regardless of required heat dissipation, the centralized architecture will need to over-size the coolant mass flow rate to ensure that downstream components can be kept cool. However, different electric components may have different temperature requirements. If the most limiting component is placed first in



(a) MTOW.



(b) Block Fuel.



(c) TMS Weight.

Fig. 9 System and subsystem level impacts of varying load electrification factor under different assumptions for electric fan efficiency. Other KPPs are assumed to take their nominal values.

Table 8 TMS weight surrogate model terms required to preserve a high goodness of fit.

Surrogate Term	Logworth
Pipe Length	784.590
Architecture	748.936
Heat Acquisition and Rejection Effectiveness (HARE)	690.663
Load Electrification Factor	649.119
Architecture $\times$ Pipe Length	390.931
Pipe Length $\times$ HARE	229.886
Architecture $\times$ HARE	220.124
Architecture $\times$ Load Electrification Factor	215.547
Load Electrification Factor $\times$ HARE	211.149
Load Electrification Factor $\times$ Pipe Length	210.818
(HARE) ²	104.249
Electric Fan Efficiency	19.899

the series, it is plausible that this maximum temperature is low enough to provide sufficient cooling to downstream components. To test this, the TMS weights are computed for both architectures while varying the temperature limit for the first component in the powertrain, the electric generator (this is also the first component to be cooled in the centralized architecture). As a comparison, a control case is run where all components are limited to the nominal value for their temperature limits: 70°C. The results of the control and the temperature-limited cases are shown in Fig 10.

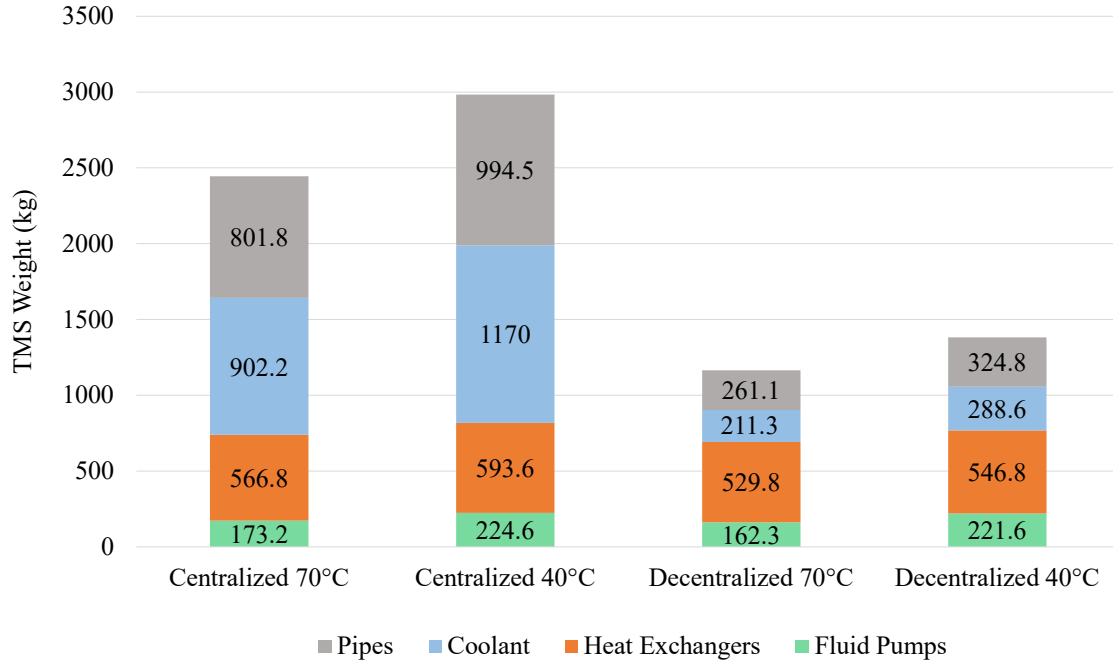


Fig. 10 Thermal management system weights for the notional testbed, assuming nominal KPP values. Combinations of centralized and decentralized architectures are shown, where the first component in the powertrain, the generator, is limited to either 70°C or 40°C. All other components are limited to their nominal value of 70°C.

Similar to the previous study, total pipe length is equal between the two architectures, but is divided into four equal segments for the decentralized architecture. Figure 10 shows that in any case, increasing the cooling requirements by reducing the maximum operating temperature of the generator increases the subsystem weight, further increasing the

block fuel required by each case. Quantitatively, this results in an increase in block fuel from 14,497 kg to 15,046 kg and an increase in MTOW from 75,867 kg to 78,934 kg for the centralized architecture. The decentralized architecture sees an increase in block fuel from 14,074 kg to 14,545 kg, and an MTOW increase from 71,742 kg to 73,613 kg. The increase in TMS weight is primarily driven by the increase in required mass flow, as seen in Table 9. The similar total mass flow requirements require similar fluid pump masses, and the similar total heat loads require similar sized heat exchangers between the architectures. Although, because the higher coolant requirement scales the weight of the entire coolant and plumbing components multiplicatively, the drawbacks of using a centralized architecture are seen clearly. However, the increases in plumbing and coolant weights in the centralized architecture are *relatively* less than those of the decentralized. The centralized architecture sees 24.0% and 29.7% increases in pipe and coolant weights respectively, while the decentralized architecture sees 24.4% and 36.6% increases. Although this may appear promising, cooling electric components below 40 °C requires sizing a larger TMS, meaning that the regime in which the centralized architecture would theoretically outperform the decentralized architecture is likely outside the realm of closed designs.

Table 9 Coolant mass flow requirements for the centralized and decentralized TMS architectures under different maximum operating temperature assumptions for the electric generator on the notional testbed.

Loop Index	Centralized 70°C	Centralized 40°C	Decentralized 70°C	Decentralized 40°C
1	28.9 kg/s	37.4 kg/s	7.29 kg/s	16.6 kg/s
2	–	–	6.93 kg/s	7.15 kg/s
3	–	–	6.58 kg/s	6.79 kg/s
4	–	–	6.25 kg/s	6.45 kg/s
Total	28.9 kg/s	37.4 kg/s	27.0 kg/s	36.9 kg/s

V. Conclusion and Future Work

This work introduces a novel graph-based methodology for thermal management system modeling, intended for conceptual aircraft design. This methodology is adaptable to any propulsion (or otherwise heat-producing) system architecture. It is parameterized through an adjacency matrix and a component-type vector. Its adaptation is enabled through sequential construction of thermal management system components which affect the temperature of a coolant or refrigerant. These connections and their analytic partial derivatives are described in detail.

This methodology can be used with any component weight, heat production, drag, and power consumption models. This work introduces models which utilize a combination of previously established and original key performance parameters to define component impacts on the subsystem, and by extension the aircraft as a whole. It was validated at the subsystem against thermal management systems in aircraft concepts from literature level using specific heat rejection as the performance metric. This validation showed that while several factors influence this performance, the methodology is able to capture the range of specific heat rejections from other works.

The methodology was used to characterize two thermal management system architectures which are representative of two design philosophies: a centralized architecture which cools components in series, and a decentralized architecture which cools components individually. For a notional partially turboelectric single-aisle testbed, the decentralized architecture was shown to outperform the centralized architecture as the coolant does not become saturated with heat before entering components further downstream in the architecture. Piping length, heat acquisition/rejection effectiveness, and fan efficiency were found to be the most influential key performance parameters on subsystem weight. While load electrification factor has an impact at both the system level and subsystem level, the magnitude and sign of this impact depends on propulsor efficiency. The benefit of electrification must not only buy its own way onto the vehicle, but that of the thermal management system as well.

Finally, a study was performed to test the effect of varying temperature limits on upstream components between the two architectures. While it is true that the centralized architecture grows relatively slower in weight than the decentralized architecture as maximum operating temperatures are lower, the absolute scale of the growth prevents the centralized architecture from outperforming the decentralized architecture in realistic operating regimes.

Continuing work includes more detailed modeling of an active cooling system component. At present, "heat pump" refers to a single component which is parameterized by a constant efficiency. Instead, a thermodynamic cycle model should be introduced to calculate the weight and power requirements for switching from a single phase coolant system

to a two phase refrigeration cycle. Future work will validate the methodology against detailed aircraft concepts at the system level, attempting to recreate several architectures under a single methodology.

Appendix

Appendix A: Testbed Design Mission and Subsystem Models

The aircraft optimized in this work are modeled using the MDAO framework described in Kaneko et al. [20], which comprises a library of multi-fidelity subsystem models. For use in parameter sweeps intended to perform hundreds or thousands of aircraft design optimizations, it is advantageous to use simplified subsystem models. This is because simplified subsystem models are more robust, as they introduce fewer design variables and constraints into the optimization problem. Additionally, the reduced complexity decreases computation time.

As discussed in Section IV, the propulsion system performance is modeled using engine decks generated in PyCycle [32]. The aerodynamics model used for the parameter sweeps assumes a constant user defined parasitic drag coefficient of 0.02, and induced drag calculated using the FLOPS method as implemented in Aviary [28]. Drag from the TMS air ducts, if they exist, is added to this computed drag before being passed to the power requirement calculation. The weight model is a surrogate model outlined in Arnson et al. [34], which requires a separate weight model for the propulsion system. Power component weights scale as linear functions of maximum component power, and they are given in Table 10. Electrical and mechanical fan weights are approximated using the propeller weight model outlined in Torenbeek [35] section 8.4.

Table 10 Linear weight models for powertrain components, excluding ducted fans.

Component	Power density (kW/kg)
Turboshaft	4.54
Generator	13.15
Rectifier	9.13
Inverter	15.47
Motor	13.15

As outlined in Section IV, the design mission for the studies in this work is 2,500 nautical miles carrying a 29,800 lb payload. The mission does not include taxi, landing, reserve, or diversion segments, although a 2,000 kg fuel allotment is included. The purpose of the mission simplification is to simplify the optimization problem, improving robustness and convergence time. The full mission is outlined in Table 11 below.

Table 11 Design mission for the notional single-aisle testbed.

Segment	Initial Altitude (ft)	Final Altitude (ft)	Initial Mach Number	Final Mach Number
Climb	0	35,000	0.3	0.77
Cruise 1	35,000	35,000	0.77	0.77
Cruise Climb	35,000	37,000	0.77	0.77
Cruise 2	37,000	37,000	0.77	0.77
Descent	37,000	0	0.77	0.3

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