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System Health Management for a Series/Parallel Partial Hybrid Powertrain With Distributed Electric Propulsion

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Abstract

Electrified aircraft powertrains contain multiple interacting subsystems, making them much more complex than traditional aircraft propulsion systems in terms of integration and control. Electrification enables aircraft to have distributed thrust-producing fans that the flight control system can leverage for enhanced maneuverability, further increasing the control complexity. A NASA concept aircraft, the SUbsonic Single Aft eNgine (SUSAN) Electrofan, is such a vehicle. SUSAN is a series/parallel partial hybrid-electric single-aisle transport aircraft that takes advantage of its electrified powertrain to provide fuel burn and emissions benefits when compared to the state-of-the-art. Achieving these benefits requires an appropriately designed control architecture that coordinates the various powertrain and flight control subsystems. As such, the SUSAN aircraft is designed with a high level of automation, allowing it to properly manage coupled subsystems and react rapidly to failures and anomalies. To do this effectively, algorithms that perform component health management, fault detection, isolation, and accommodation, and continuous optimization, must be developed and implemented. This paper describes the development of some of these algorithms for system health management applied to the powertrain of the SUSAN concept aircraft.

1.0 Introduction

The SUbsonic Single Aft eNgine (SUSAN) Electrofan (Figure 1) is a subsonic regional jet transport aircraft concept with a 2040 entry-into-service date. It utilizes electrified aircraft propulsion (EAP) to enable propulsive and aerodynamic benefits to reduce fuel usage, emissions, and cost. The target market is the regional low-cost carrier airline with mission specification: 180 passengers, design range of 2500 miles, economic range of 750 miles, cruise speed of Mach 0.785 (Ref. 1). The details of the concept are evolving, but the consistent features include a single boundary layer-ingesting (BLI) turbofan gas turbine engine (GTE) with generators driving a series/parallel partial hybrid EAP system (Figure 2). The

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Figure 1.—Rendering of the current version of the SUSAN concept aircraft.

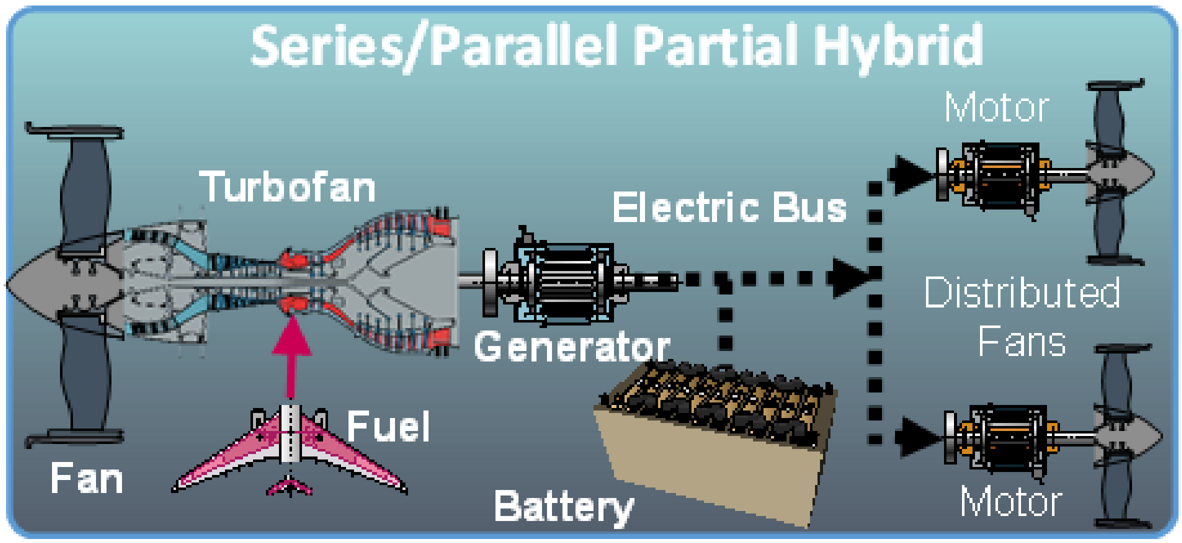

Figure 2.—Series/parallel partial hybrid EAP architecture.

current iteration of SUSAN has 16 underwing contrarotating BLI fans (also called wingfans or Electric Engines (EEs)), eight on each side. Note that for this paper, Electric Engine is used to mean the entire contrarotating BLI fan, including the electric motor, controller, etc., used as the source of propulsion. Generally, a single GTE would present a certification problem as an engine failure could prove catastrophic. The SUSAN concept attempts to overcome this obstacle with single-use (primary) batteries that provide emergency power to the EEs in case of GTE or generator failure. Relatively small reusable (secondary) batteries are also present to enable various EAP benefits. A diagram of the powertrain is shown in Figure 3 (Ref. 1). To fully achieve the potential benefits of the design, a control system needs to coordinate the operation of the subsystems (Ref. 2). A system that fulfills the potential of electrification must meet integration and operational requirements that depend on all parts working properly together. In some cases, faults in one subsystem can severely impact other subsystems, much more so than in aircraft with traditional powertrains (Ref. 3). This requires special algorithms to monitor, detect, and mitigate faults. This paper discusses some potential System Health Management (SHM) algorithms applied to the SUSAN powertrain that demonstrate component health management including response to faults.

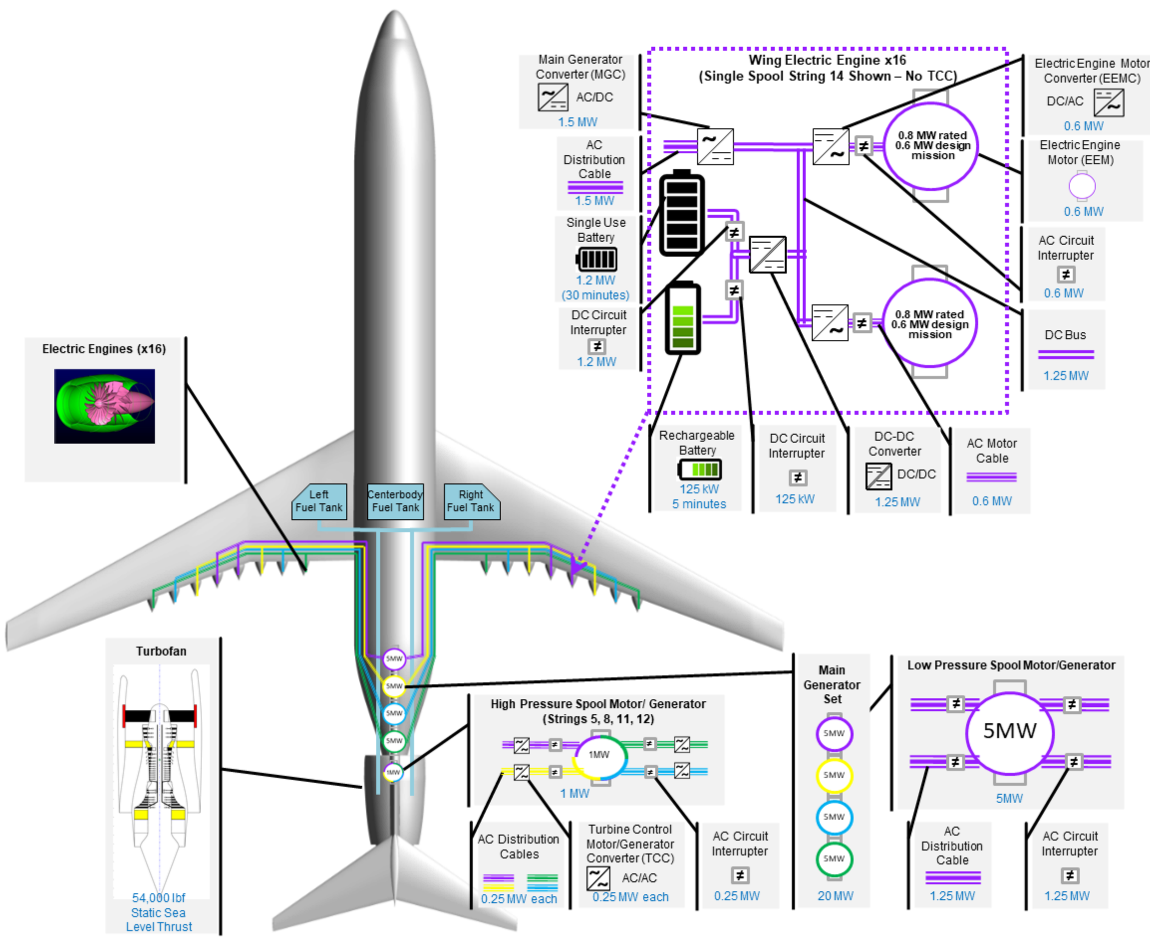

Figure 3.—Diagram of the SUSAN powertrain.

The rest of this paper is organized as follows. In Section 2.0, the powertrain is described. Section 3.0 defines SHM in the context of this paper. This is followed by a description of several preliminary algorithms in Section 4.0. Section 5.0 contains a discussion of SHM as it relates to the SUSAN powertrain, and Section 6.0 presents conclusions.

2.0 Powertrain Design

The fully integrated nature of the SUSAN vehicle makes the powertrain functionality central to the control design effort. As shown in Figure 3, the powertrain in its current configuration includes a single BLI GTE in the tail. Power is extracted from it through four 5 MW motor/generators (electric machines or EMs) connected to the Low-Pressure Spool (LPS) and a single 1 MW EM on the High-Pressure Spool (HPS). These generators are connected to buses that distribute power to operate the 16 EEs under the wings. The engines are numbered 1 to 17 from left to right from the pilot’s point of view, with the centrally located GTE identified as number 9. Four three-phase power buses from each of the 5 MW main generators connect to four EEs symmetrically across the wings (1, 8, 10, 17), (2, 7, 11,16), (3, 6, 12,15), and (4, 5, 13, 14), as shown in Figure 4. This ensures that a generator failure will not result in thrust asymmetry. The 1 MW generator also has four three-phase power buses, one each attached to a single EE tied to each of the main generators (5, 8, 11, 12) (not shown in Figure 4). Although four buses share each generator, the power for each bus is demanded independently up to its current limit or the total power

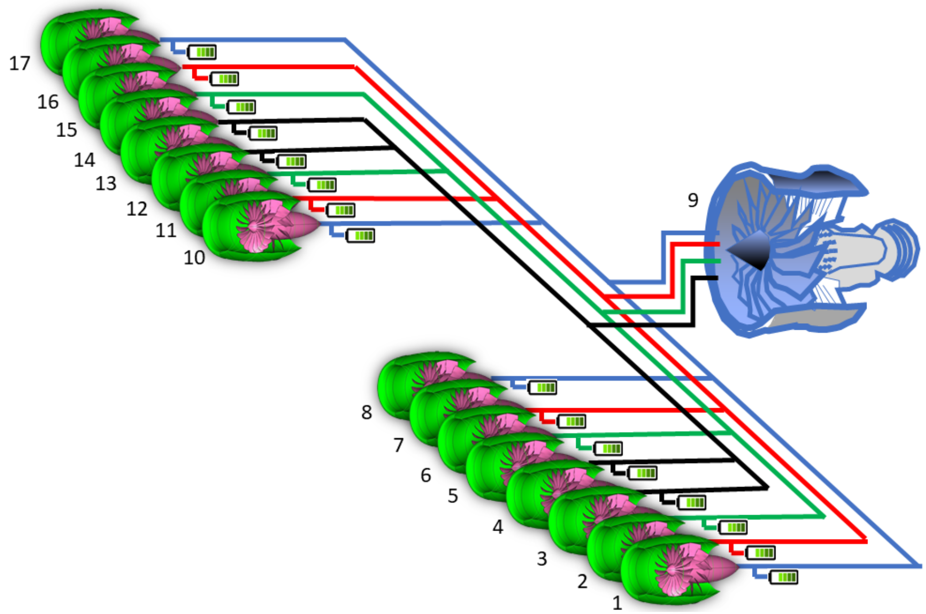

Figure 4.—SUSAN powertrain showing engine numbering and four symmetric buses connecting the LPS generators to the EEs.

limit of the generator. The components are designed such that throughout the flight envelope, 1/3 of the aircraft's thrust is supplied by the GTE and the EEs supply the remaining 2/3, which requires a large amount of power extraction. A small rechargeable battery is attached to each bus through a DC-DC converter. This battery has multiple functions related to control and operation of the aircraft, including providing a boost capability during climb, enabling rapid acceleration of the EEs, facilitating GTE operability improvements, and helping to maintain bus voltage.

Unlike a traditional multiengine aircraft in which pilots have individual throttle levers they can manipulate independently, the SUSAN powertrain operation is complex, and no pilot intervention is permitted beyond the movement of a single throttle lever (Ref. 4).[1] Furthermore, distributed propulsion provides enhanced maneuverability that the flight control system can leverage. These interactions require the control system to coordinate multiple subsystems simultaneously while respecting the constraints of each. This coordination optimizes overall operation, which subsequently enables potential weight reduction benefits.

3.0 System Health Management

An Integrated Vehicle Health Management (IVHM) system requires a multidisciplinary approach that enables automatic detection, diagnosis, prognosis, and mitigation of adverse events arising from component failures (Ref. 5). SAE International calls this a Self-Adaptive Health Management System, which they define as self-adaptive control and optimization to extend vehicle operation and enhance safety in the presence of potential or actual failures (Ref. 6). This is the highest of SAE's six IVHM capability levels. Many other definitions of IVHM exist, including for applications to a specific component rather than to the vehicle as a whole and, paradoxically, those that do not require integration (Ref. 7). For this paper, because the scope is limited to the powertrain, the term SHM will be used to correspond to the SAE definition above. In the context of the SUSAN powertrain, the SHM system

[1]Based on the current nominal concept of operations. However, this remains an area of on-going research.

monitors the GTE, the power system, and the EEs. While the airframe might employ structural health monitoring, sensor and actuator health monitoring, etc., these topics will not be discussed in this paper. The SHM system detects, isolates, and can help accommodate faults. It provides prognostic information that supports mission modification, if necessary. The SHM system supports redistribution of power to EEs in case of specific motor failures, and control reconfiguration in general. With SUSAN it is anticipated that a vast array of potential powertrain faults will be handled automatically up to the limits of the system. The built-in redundancy allows EE failure and potentially even a generator failure to be accommodated without a significant performance impact, and a GTE failure is mitigated using the primary batteries, although this is an emergency situation.

The SUSAN design attempts to reduce aircraft emissions by 50 percent per passenger mile while retaining the size, speed, and range of a large regional jet (Ref. 1). This is achieved through a variety of optimizations including control approaches that enable size and weight reductions. For example, the use of Distributed Electric Propulsion (DEP) for maneuvering allows the rudder size to be reduced. This reduces not only the weight of the rudder, but that of the related tail structure and its actuators. However, rudder sizing and travel are typically defined by requirements for minimum-controllable airspeeds following an engine failure and crosswind limits for takeoff and landing (Ref. 8). Thus, any resizing must be accompanied by the assurance that the enabling design change, DEP in this case, will be sufficiently reliable that acceptable safety margins are not compromised. In this way, SUSAN trades redundancy of one type for that of another. Instead of having oversized parts, for example two engines each individually capable of safely powering the aircraft (as is the case in current aircraft), SUSAN relies on multiple smaller components, a complex control system to coordinate it all, and a comprehensive, robust SHM system to ensure highly reliable, optimized operation.

4.0 System Capability Development

Although the SUSAN design is still maturing, the architecture of the powertrain is essentially fixed. Details such as the number and placement of the EEs could change, but the generic types of SHM and optimization approaches being developed at this stage of the effort remain valid given any foreseeable structural updates. Thus, successful algorithms could be incorporated into a larger system. Several preliminary estimation and control optimization algorithms that address specific objectives have been developed and evaluated; they are described below. It is anticipated that some version of these could be used to support higher level functions within a comprehensive SHM and optimization system.

A dynamic model of the SUSAN aircraft, including a detailed model of the powertrain (Ref. 9) and the complex control system that coordinates its operation (Ref. 2), provides the testbed for the algorithms. It also provides data for machine learning approaches.

4.1 Coordinated Turn Optimization

In the baseline SUSAN model, the integrated flight and propulsion control system commands the flight control surfaces, the EEs, and the GTE's throttle to maneuver (Ref. 10). In this case, reinforcement learning, which works by determining the best output for a given input by observing the response of the environment to that output, was used to train a flight controller to perform a coordinated turn while minimizing control surface deflection, a proxy for minimizing drag (Ref. 11). Here the reinforcement approach learned how to control the rudder, EEs (as eight opposing pairs controlled differentially), and ailerons, while leaving the baseline flight control in place to command the elevators and throttle. The controller successfully learned to match relevant aircraft variables throughout the turn while minimizing control surface deflection without increasing thrust (power consumption). Figure 5 shows the roll, roll

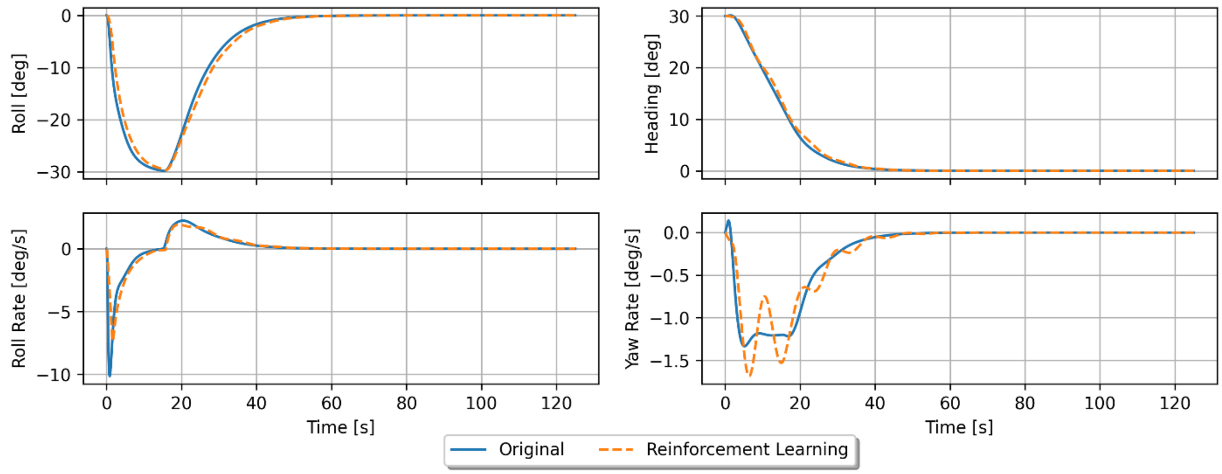

Figure 5.—Relevant aircraft variables during a coordinated turn, comparing the baseline flight control system and the reinforcement learning algorithm.

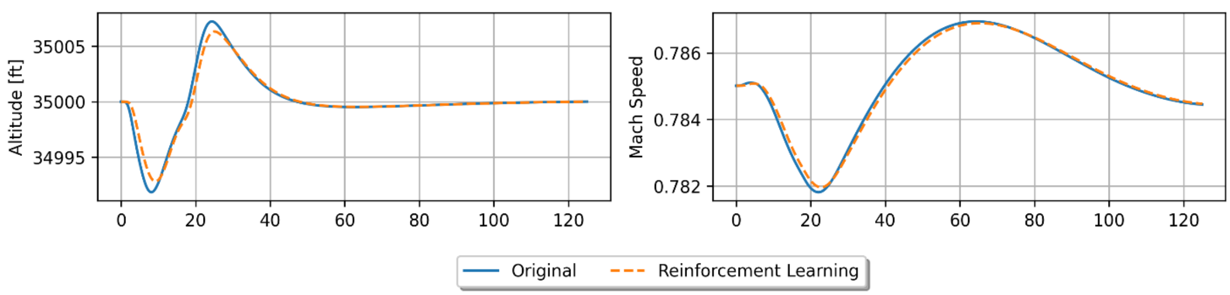

Figure 6.—Altitude and speed variation during a during a coordinated turn, comparing the baseline flight control system and the reinforcement learning algorithm.

rate, heading, and yaw rate from the original flight control, and that obtained through machine learning. Roll, roll rate, and heading are very similar, although the initial excursion in the “learned” roll rate is noticeably less. The “learned” yaw rate is significantly more oscillatory than the baseline, though the magnitude of the oscillation is quite small. Figure 6 shows the variation in altitude and speed during the coordinated turn. The baseline control and the reinforcement learning control match quite closely, with little variation in either variable. However, the variation exhibited with the reinforcement learning control is slightly less. Figure 7 shows the rudder and aileron movement as well as the thrust from the individual EEs and the GTE. The “learned” rudder and aileron deviations are significantly less than those produced by the baseline flight control system, with the rudder remaining very near its nominal position throughout the coordinated turn. The fact that the “learned” rudder response was nearly zero is not surprising, the original flight control law has an option to vary the allocation of control authority between the rudder and the EEs, allowing some or all of the rudder function to be assigned to the EEs (Ref. 10). However, when taken in combination with the thrusts, the result is quite surprising. There are several things to notice about the thrusts. First, the GTE thrust in both cases is very similar, which is because it is commanded by the baseline flight control. Second, in both cases the average EE thrust curve tracks the GTE thrust curve, which is expected because the power extraction for the EEs (which is related to their thrust produced) is set by the power level and thus thrust of the GTE. What is quite remarkable is that the spread of the differential pairs is much less in the “learned” case than with the baseline control. This means that the reinforcement approach achieves a very similar coordinated turn to the baseline control but with both less rudder movement and less thrust differential, although the total thrust is essentially the same. One thing to

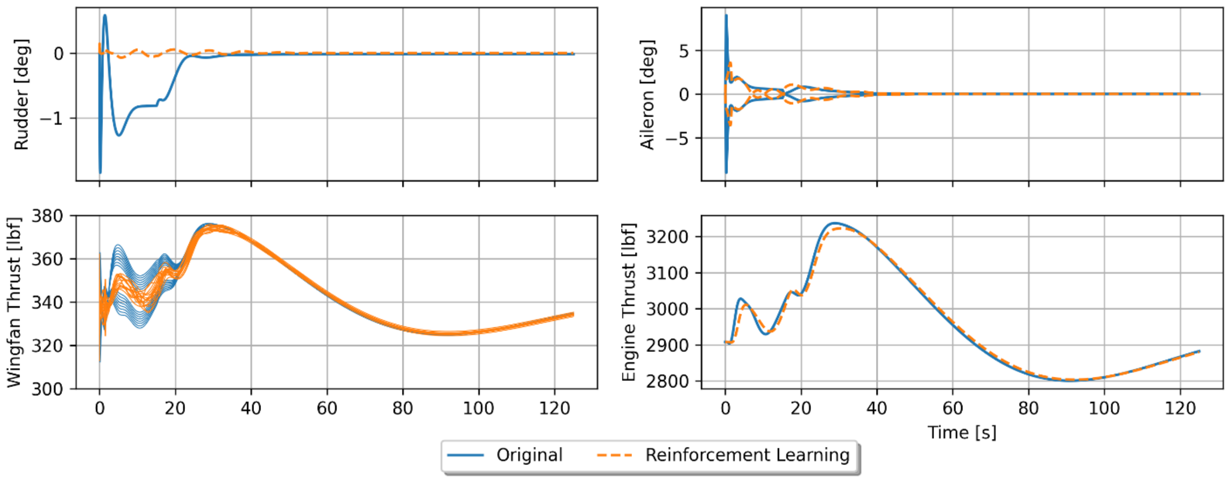

Figure 7.—Rudder, aileron, wingfan (electric engine) and GTE thrusts during a coordinated turn, comparing the baseline flight control system and the reinforcement learning algorithm.

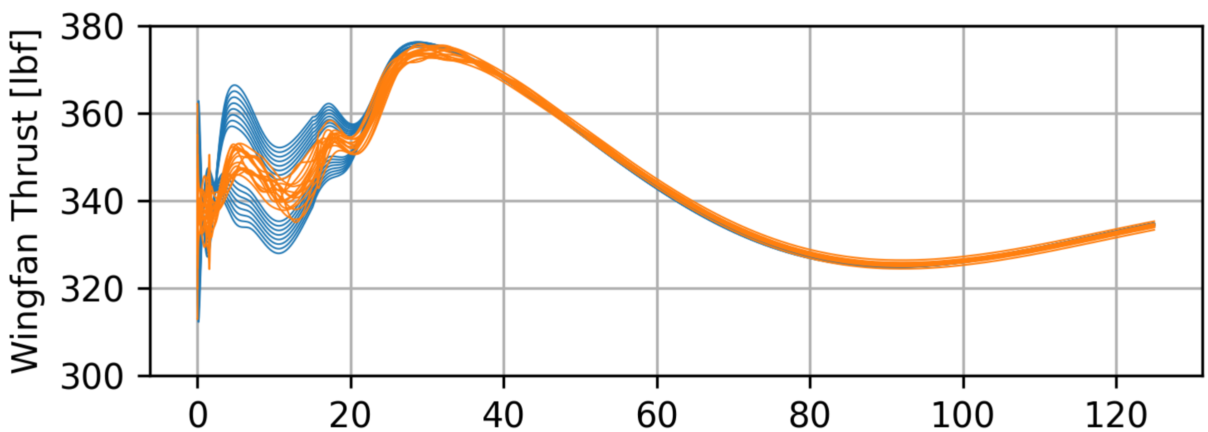

Figure 8.—Wingfan (electric engine) thrusts during a coordinated turn, comparing the baseline flight control system and the reinforcement learning algorithm.

note in Figure 8, which is an expanded view of the lower left plot in Figure 7, is that while the baseline flight control provides evenly distributed EE commands, the reinforcement learning control commands to the differential pairs are more jumbled and actually crisscross throughout the turn. The apparent advantage of this specific learned result for a coordinated turn may warrant further investigation.

4.2 Compensation of Failed EE With DEP

The appropriate response to failures is a fundamental aspect of a health management system. SUSAN's architecture provides sufficient redundancy to overcome one and potentially multiple EE failures. The 16 EEs are aligned, so the thrust lost due to any individual failure can be made up by adjusting the thrust from other EEs. This is subject to the constraint that any thrust imbalance created by the failure must be compensated by ensuring that the torque on the aircraft is maintained. Furthermore, it must be accomplished within the bounds of powertrain operation, specifically that the EEs stay within their operating range and that the power draw stays within its acceptable range.

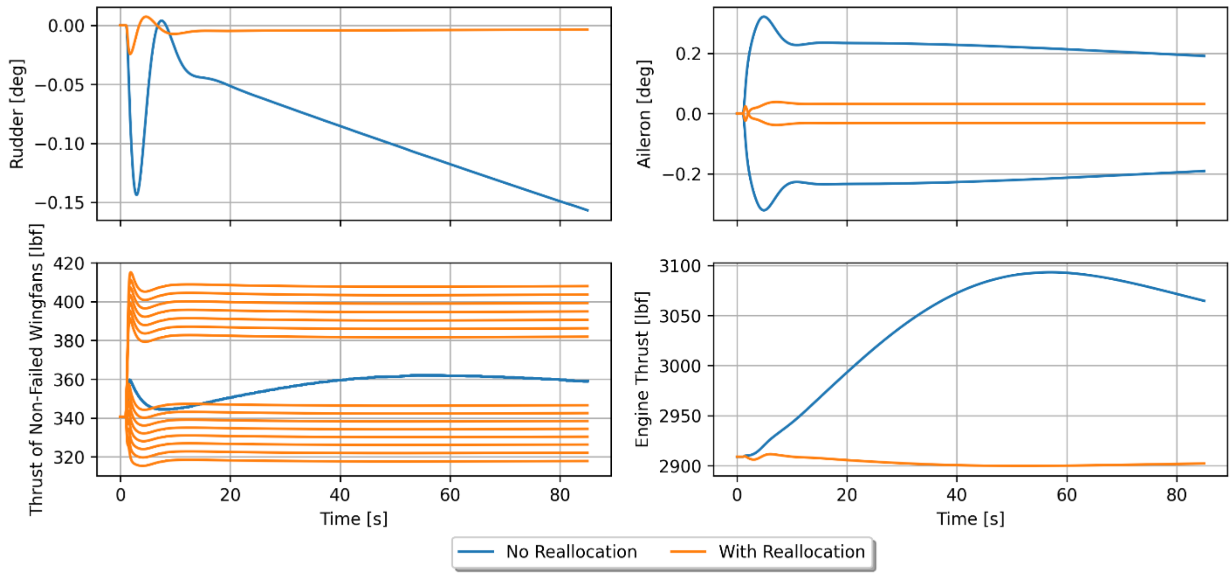

Figure 9.—Reinforcement learning control and baseline control with an EE failure. The baseline control without reallocation of thrusts to the remaining wingfans (EEs) must compensate with the other effectors.

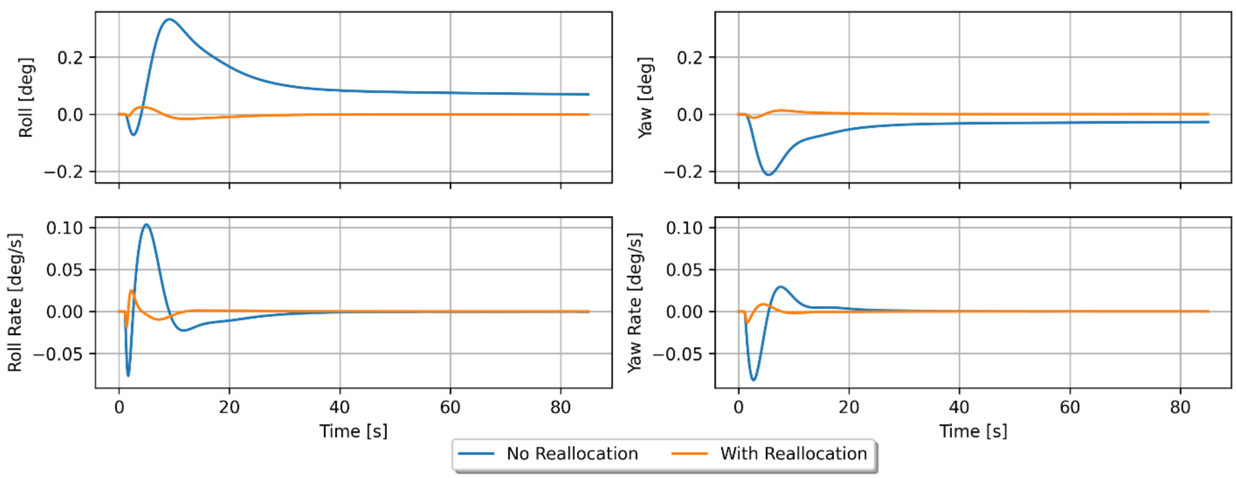

Figure 10.—Reinforcement learning control and baseline control with an EE failure. The baseline control without reallocation of thrusts to the remaining EEs allows much larger excursions in aircraft variables than the reinforcement learning control.

Here again reinforcement learning was used to develop a flight controller that accommodates an EE failure, which is assumed to have been detected and isolated. Figure 9 compares the reinforcement learning control (with reallocation of the thrust from the failed EE (#1 in Figure 4) to the working EEs) to the baseline control (no reallocation). Note that the baseline control must use the flight control surfaces and engine thrust to compensate for the lost thrust and resulting thrust imbalance. Figure 10 shows how the reinforcement learning control greatly reduces the excursions of certain aircraft variables from steady state compared to the baseline control.

There are two interesting observations to be made here. First, the specific reinforcement learning implementation, in which the remaining EEs are each assigned a portion of the lost thrust according to a “learned” redistribution (Ref. 11), resulted in evenly spaced thrust curves, much more reminiscent of the baseline control than of the “learned” differential pair commands in Figure 8. Second, while data-driven

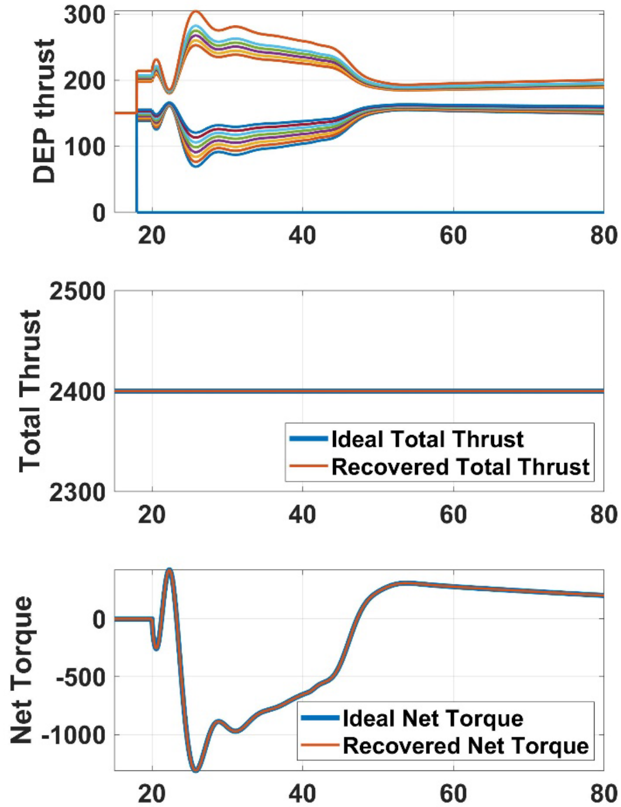

Figure 11.—Example using DEP for turning. Here EEs #15 and #16 (Figure 4) fail at 18 s, resulting in thrust reallocation to the remaining EEs.

approaches offer advantages for control applications, for example, capturing unmodeled dynamics, using the simplest approach is often best (Ref. 12). The control reallocation problem in particular lends itself well to a model-based approach known as a control mixer, which has a history of use in the area of flight control reconfiguration in response to actuator failures (Ref. 13). Not surprisingly, the results of the two approaches are similar. Figure 11 shows the notional EE commands for a coordinated turn after a double EE failure (#15 and #16 in Figure 4), which are assumed to have been detected and isolated. The lower plots show how, using those thrust commands, thrust would be maintained and the imbalance eliminated. Because the results in Figure 11 are based on commands, they do not account for the aircraft dynamics nor the resulting control surface compensation. However, it is clear from the matching that any disturbance would be minimal.

4.3 EE String Efficiency Estimation

So far, the example algorithms have demonstrated control optimization (not strictly SHM) and control reconfiguration in response to a failure. This example investigates estimation of the efficiency of an electrical string associated with an individual EE. A string comprises all components from the main generator attached to the GTE to the EE motor (Figure 3). For this effort, a string was modeled using the Electrical Modeling and Thermal Analysis Toolbox (EMTAT) (Ref. 14). The EMTAT blocks were parameterized to represent the type of electrical power system components anticipated to be available at the time SUSAN would be entering into service. For feasibility, these components are each projected to require percent efficiencies in the high 90s (Ref. 15). Thus, the parameterization resulted in an efficiency

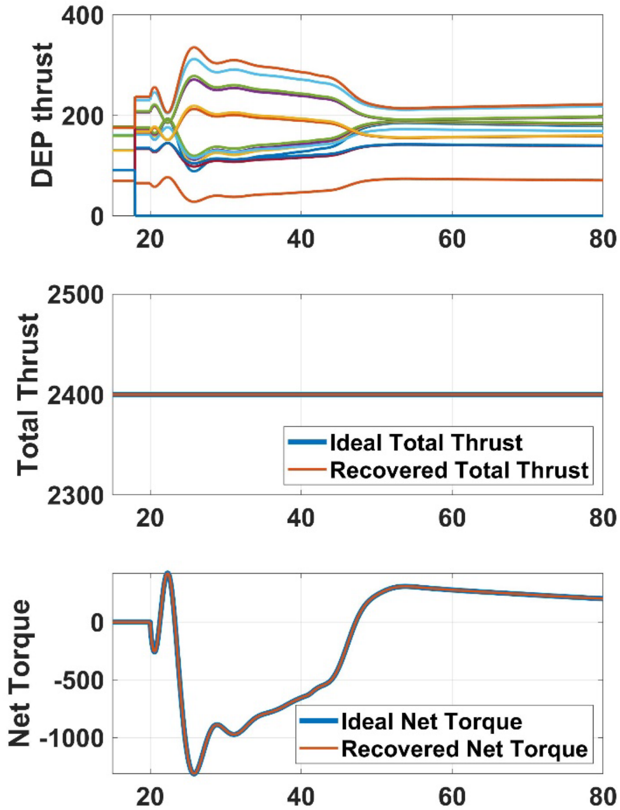

Figure 12.—Example using DEP for turning accounting for the efficiency of each string. Here EEs #15 and #16 (Figure 4) fail at 18 s, resulting in thrust reallocation to the remaining EEs.

of the entire string generally above 90 percent, with variation assumed due to manufacturing differences and other factors. A deep learning artificial neural network was trained to estimate the string's efficiency from sensed variables using data generated from the model. The estimation accuracy was found to be within 1 percent.

This information can be used to support the previously discussed algorithms. With knowledge of the efficiency of each EE string, the healthier strings, i.e., the ones that require less overall power and will therefore cause less wear and tear on the GTE, can be utilized more heavily. Figure 12 shows the same scenario as Figure 11, but accounts for the efficiency of each string. One can immediately see that initially, before the failures, the EE thrust commands are separate, rather than being all the same. Also, they are not evenly spaced, implying that the least efficient strings are penalized in favor of the more efficient strings. Even with this skewed EE utilization, the total thrust and net torque on the aircraft match that for an ideal coordinated turn.

5.0 Discussion

The SUSAN powertrain presents new problems in SHM. Health management has been applied to GTEs for decades and is a relatively mature field (Ref. 16), but the new electrified architectures introduce more failure modes due to the added complexity and number of components. The elements of the powertrain tend to be highly coupled so that the failure of one component could have a cascading effect throughout the rest of the system (Ref. 17). New SHM algorithms that address these issues are necessary to achieve the level of safety required for certification.

The example algorithms presented above are all related to DEP in some way. They directly address or support mitigation of an EE failure. Because of the redundancy in the SUSAN powertrain design, an EE failure will be considered minor by the FAA as long as continued safe operation, including in-flight handling/controllability and maneuvering, is not impacted (Ref. 18). Figure 9 and Figure 10 show the difficulty the baseline flight control has with just a single EE failure, while Figure 11 and Figure 12 demonstrate the ease with which multiple EE failures are accommodated, up to the limits of the powertrain. These examples highlight the need for and utility of a health management system, especially as it relates to certification requirements.

6.0 Conclusion

This paper described some preliminary SHM algorithms developed for the SUSAN concept aircraft and demonstrated their use. The examples leveraged the redundancy within the powertrain to achieve continued safe flight when a failure occurred. The complexity of the SUSAN powertrain and the interdependence of the parts means that the pilot will likely have no control over individual subsystems, so powertrain SHM is critical to the safe operation of the vehicle. Rather than relying on oversized parts to compensate for a failure, as is done for turbofan engines in today's aircraft, component size is minimized where possible to achieve the weight savings necessary to meet the fuel consumption goals. The function of these undersized parts is supported by other features; for instance, the rudder is aided by DEP, and the engine is augmented by battery power to the EEs. This redundancy, reinforced by a robust health management system, should make the overall powertrain operation sufficiently reliable to ensure the SUSAN concept's feasibility.

References

1. Jansen, R.H., et al., "Subsonic Single Aft Engine (SUSAN) Transport Aircraft Concept and Trade Space Exploration," AIAA 2022-2179, *AIAA SciTech Forum*, San Diego, CA, and virtual, 3–7 January 2022.
2. Litt, J.S., Kratz, J.L., et al., "Control Architecture for a Concept Aircraft with a Series/Parallel Partial Hybrid Powertrain and Distributed Electric Propulsion," AIAA 2023-1750, SciTech Forum, 23–27 January 2023, National Harbor, MD.
3. Simon, D.L., and Connolly, J.W., "Electrified Aircraft Propulsion Systems: Gas Turbine Control Considerations for the Mitigation of Potential Failure Modes and Hazards," ASME Turbo Expo 2020, Turbomachinery Technical Conference and Exposition, GT2020-16335, September 21–25, 2020.
4. Arthur, III, J.J., Kennedy. K., Etherington, T.J., Sachs-Wetstone, J.J., Litt, J.S., and Owen, A.K., "Flightcrew Thrust Control and Engine Display Concepts for the SUbsonic Single Aft ENgine (SUSAN) Transport Aircraft," *AIAA SciTech Forum*, National Harbor, MD, 23–27 January 2023.
5. Divakaran, V.N., Subrahmanya, R.M., and Ravikumar, G.V.V, Integrated Vehicle Health Management of a Transport Aircraft Landing System, white paper, https://www.infosys.com/engineering-services/white-papers/documents/aircraft-landing-gear-system.pdf
6. SAE International, Integrated Vehicle Health Management, Rev. 2, April 2018.
7. Jennions, I.K., Ed., *Integrated Vehicle Health Management: Perspectives on an Emerging Field*, SAE International, Warrendale, PA, 2011.
8. Hoh, R.H., Nicoll, T.K., and Desrochers, P., "Piloted Simulation Study to Develop Transport Aircraft Rudder Control System Requirements, Phase 2: Develop Criteria for Rudder Overcontrol" DOT/FAA/AR-10/17, 2010.

9. Litt, J.S., Sowers, T.S., Buescher, H.E., Sachs-Wetstone, J.J., Listgarten, N.L., Jansen, R.H., “Implementation Approach for an Electrified Aircraft Concept Vehicle in a Research Flight Simulator,” AIAA 2022-2306, SciTech Forum, San Diego, CA, and virtual, January 3–7, 2022.
10. Ogden, N.C., and Patterson, A., “A Framework for Evaluating Distributed Electric Propulsion on the SUSAN Electrofan Aircraft,” NASA/TM–20230009523, July 2023.
11. Wu, K.C. and Litt, J.S., “Reinforcement Learning Approach to Flight Control Allocation with Distributed Electric Propulsion,” NASA/TM-20230014863, 2023.
12. Bowman, C., Tschan, C., and Zetocha, P., “Advances in Intelligent Systems for Space Applications,” in *Advances in Computational Intelligence and Autonomy for Aerospace Systems*, John. Valasek, ed., American Institute of Aeronautics and Astronautics, Reston, VA, 2018.
13. Litt, J.S., Roulette, G., “A Method for Exploiting Redundancy to Accommodate Actuator Limits in Multivariable Systems,” NASA TM-106859,1994.
14. Bell, M.E., Litt, J.S., “An Electrical Modeling and Thermal Analysis Toolbox for Electrified Aircraft Propulsion Simulation,” AIAA 2020-3676, AIAA Propulsion and Energy 2020 Forum, August 24–28, 2020.
15. Haglage, J.M., Dever, T.P., Jansen, R.H., and Lewis, M.A., “Electrical System Trade Study for SUSAN Electrofan Concept Vehicle,” AIAA 2022-2183, *AIAA SciTech Forum*, San Diego, CA & virtual, 3–7 January 2022.
16. Litt, J.S., et al., “A Survey of Intelligent Control and Health Management Technologies for Aircraft Propulsion Systems,” AIAA Journal of Aerospace Computing, Information, and Communication 2004, vol. 1 no. 12 (543–563).
17. Kratz, J.L., and Simon, D.L., “Failure Modes and Mitigation Strategies for a Turboelectric Aircraft Concept with Turbine Electrified Energy Management,” AIAA 2022-1191, AIAA SCITECH 2022 Forum, January 3–7, 2022, San Diego, CA & Virtual.
18. Litt, Jonathan S., Sachs-Wetstone, Jonah J., Simon, Donald L., Sowers, T.S., Owen, A.K., Bell, Mark E., Guthrie, Brenden E., Lehan, Julian, and Castro, Amado, “Flight Simulator Demonstration of Powertrain Failure Mitigation in a Partial Turboelectric Aircraft,” AIAA 2023-4156, AIAA AVIATION 2023 Forum, 12–16 June 2023, San Diego, CA and Online.