# Transient Optimization of a Gas Turbine Engine

**2023 AIAA SciTech Forum**

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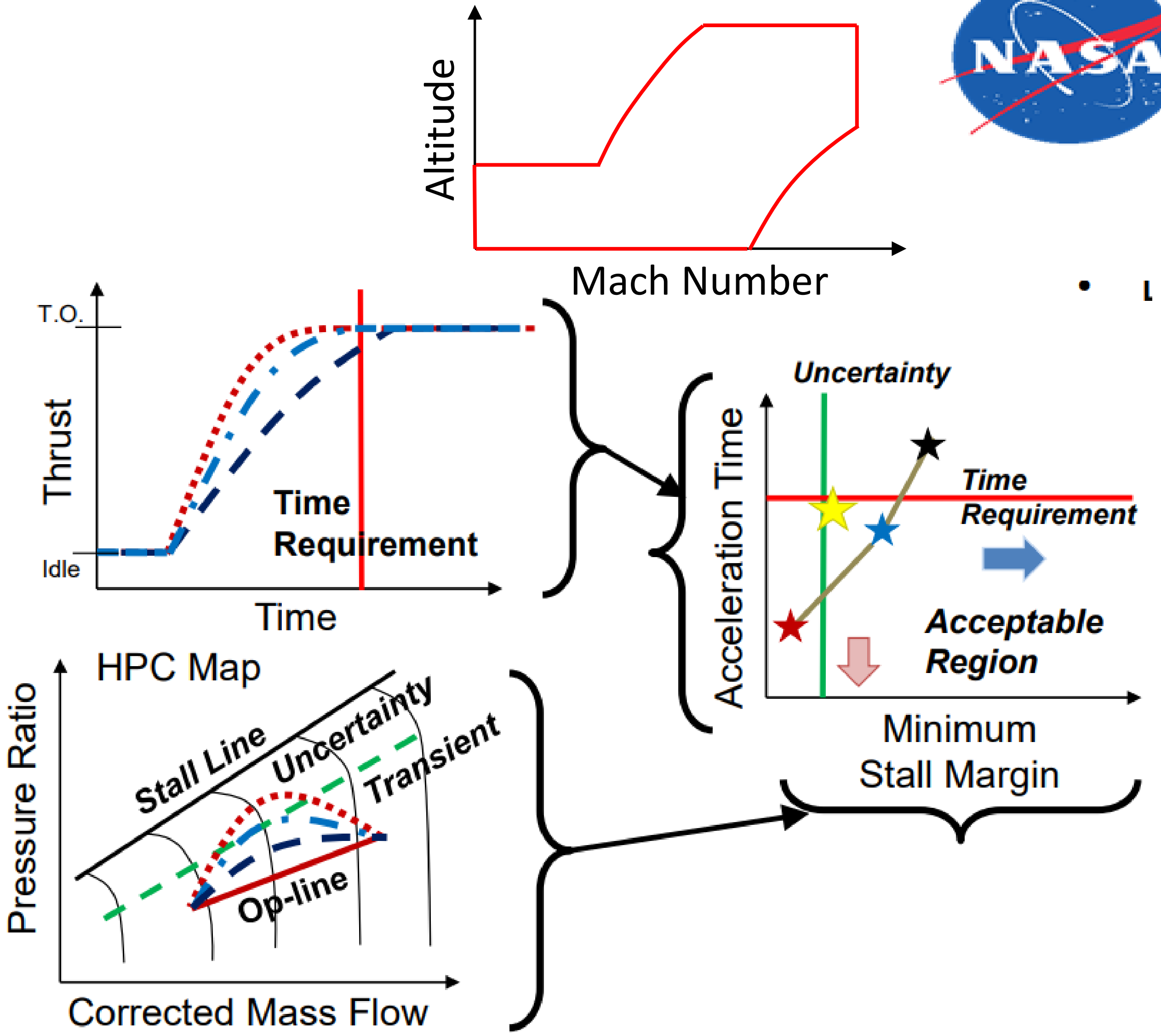
# Background

- Challenge – maintaining operability during engine power transients throughout a vast operating envelope
- Transient limit logic
  - protects the engine from compressor stall/surge and combustor blowout
  - Transient limit logic accounts for nearly 75% of the total time dedicated to control system development†
  - Is often implemented as a shaft acceleration/deceleration schedule or a ratio unit (fuel flow / compressor discharge pressure) schedule
- Control design is guided by requirements for thrust responsiveness and adequate operability margin
- Engine design and associated performance are constrained by operability requirements




†Reference: Jaw & Mattingly, Aircraft Engine Controls: Design, System Analysis, and Health Monitoring,

*Image Credit to NASA and the Tool for Turbine Engine Closed-loop Transient Analysis (TTECTrA)

# Background (cont.)

- Common techniques for transient limit logic design are sub-optimal
- Engine performance shifts with degradation and maintenance → an optimal design is only optimal for a specified health state
- Digital twin technology can be leveraged to design and potentially update controls
- Optimization techniques could be applied to refine the transient limit logic
- Machine learning can be applied to update the logic as the engine ages to maintain near optimal dynamic performance

**REAL ASSET**

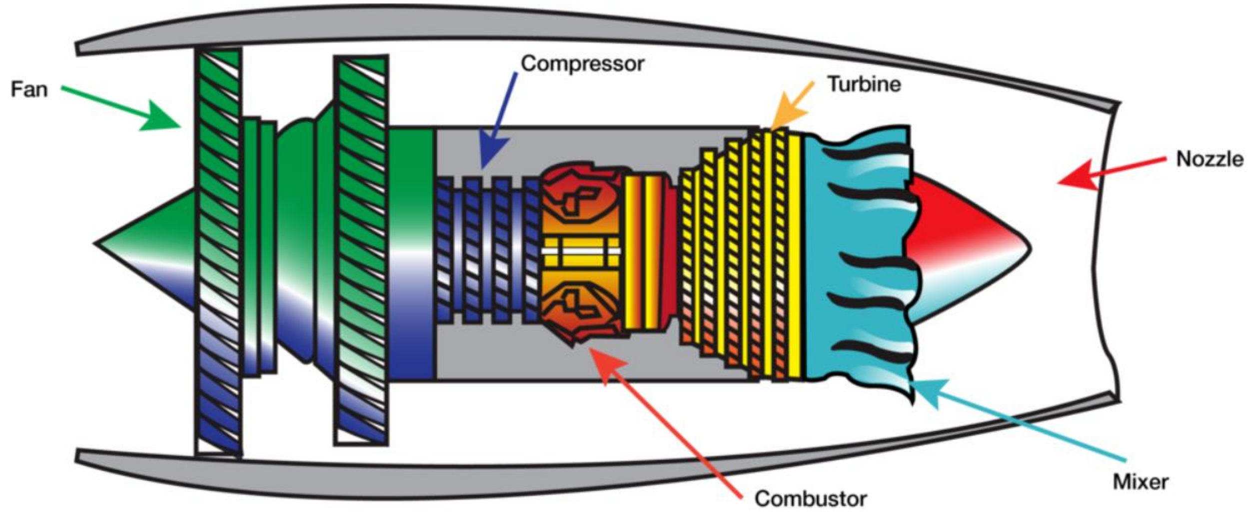



Image Credit: NASA

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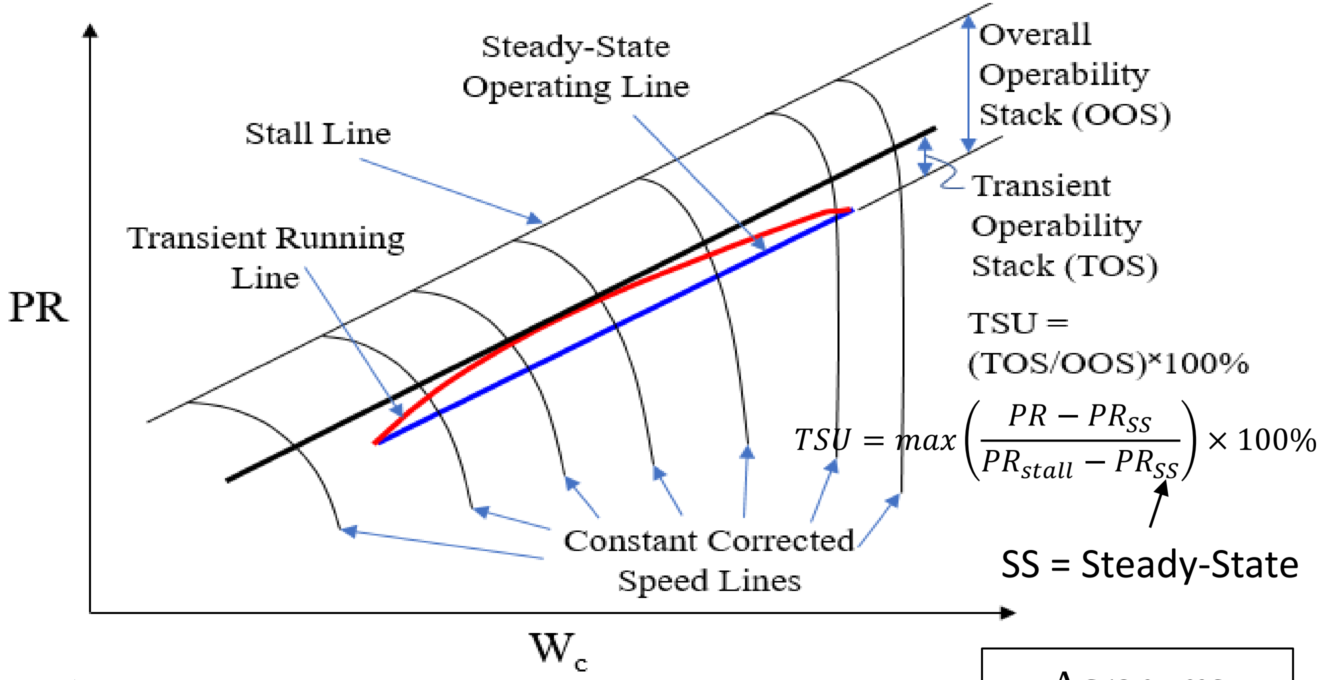
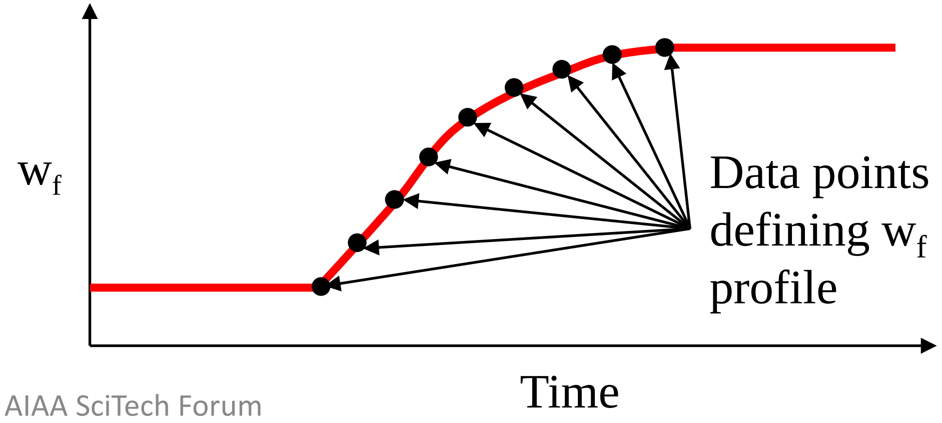
**DIGITAL REPRESENTATION**

# The Optimization Approach

- A genetic algorithm is applied to identify the "optimal" fuel flow rate profile that maximizes operability as defined by the transient stack usage (TSU)
    - applies functions of elitism, carry-over (replication), cross-over (reproduction), and immigration
    - utilizes rank-based selection with probabilities based on a pareto distribution
- The inputs are the fuel flow values at various times throughout the transient, constrained to be monotonically increasing or decreasing
- An iterative root solving technique is leveraged to stretch/compress the fuel flow input profile to achieve the desired thrust response time
- Use optimized results to derive transient limit schedules

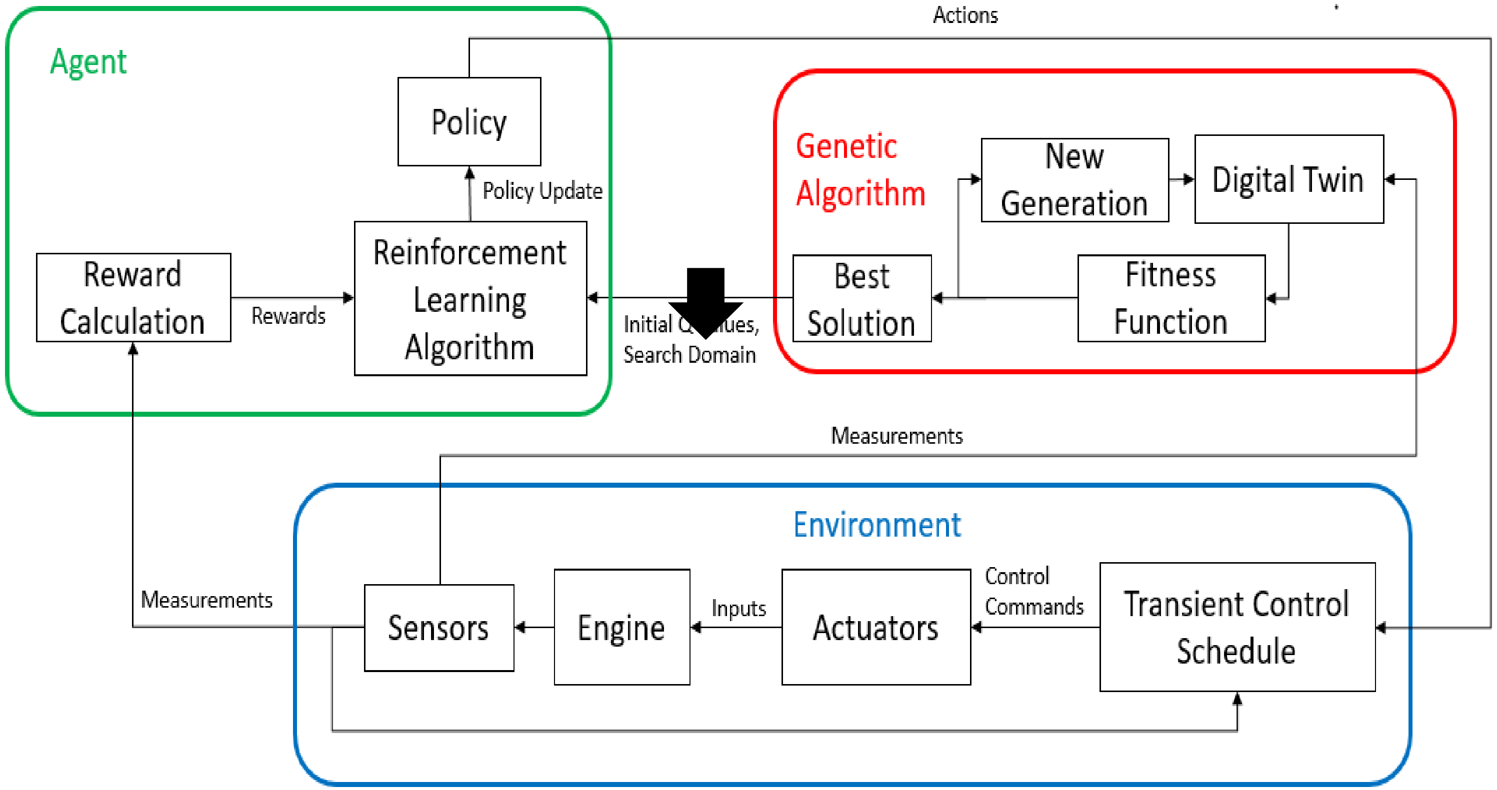



Acronyms
PR = pressure ratio
$W_c$ = corrected flow rate
$w_f$ = fuel flow rate

# The Engine Lifespan Optimization Approach

- Use the digital twin to
  - Design a conservative schedule for an end-of-life (EOL) engine
  - Design an aggressive schedule for a new (NEW) engine
  - Create an array of discrete schedules between the two extremes
  - Could update the "aggressive schedule" and discrete options over the lifespan of the engine
- Use a reinforcement learning (RL) algorithm to shift the schedule in small increments and accumulate rewards based on sensor feedback



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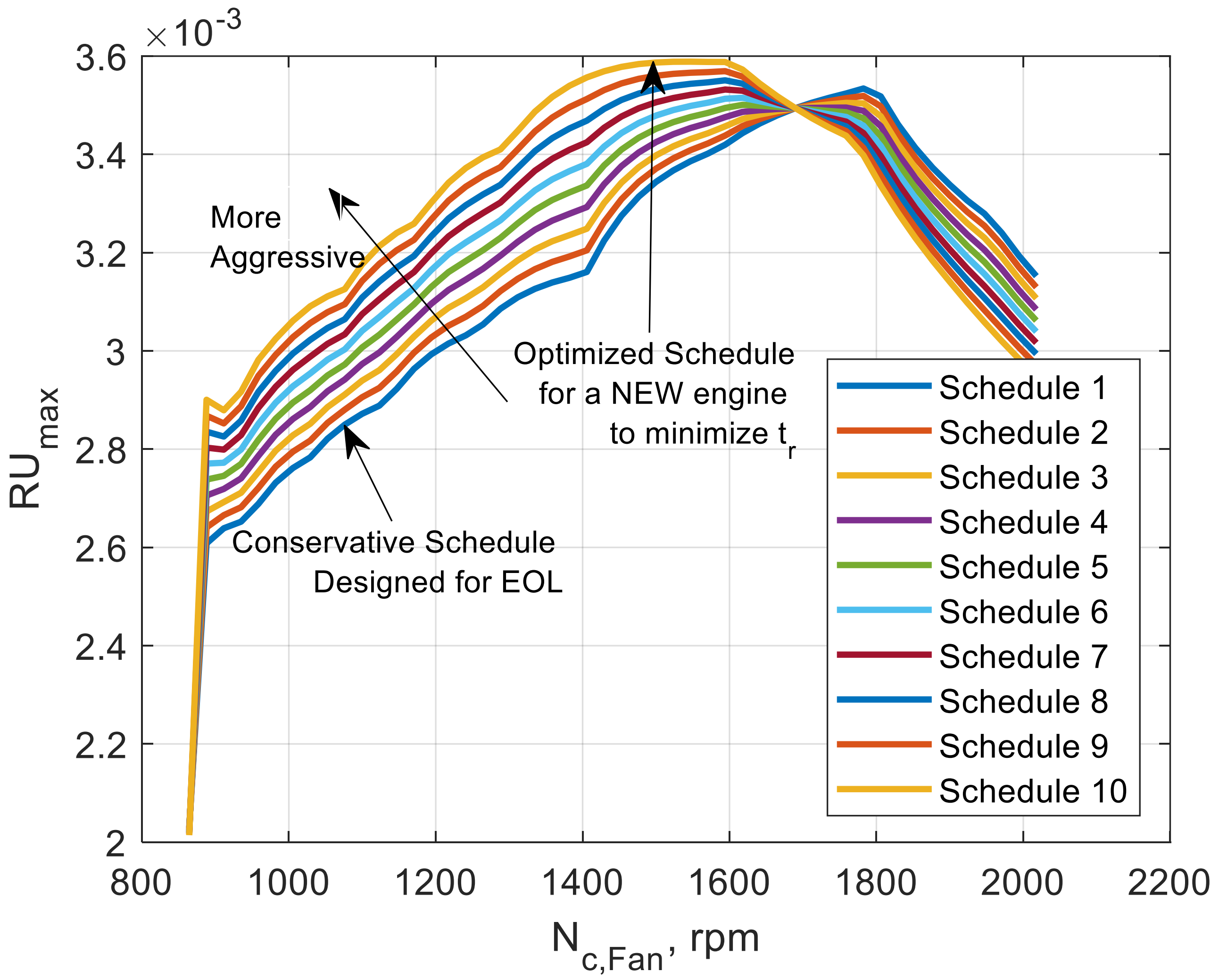
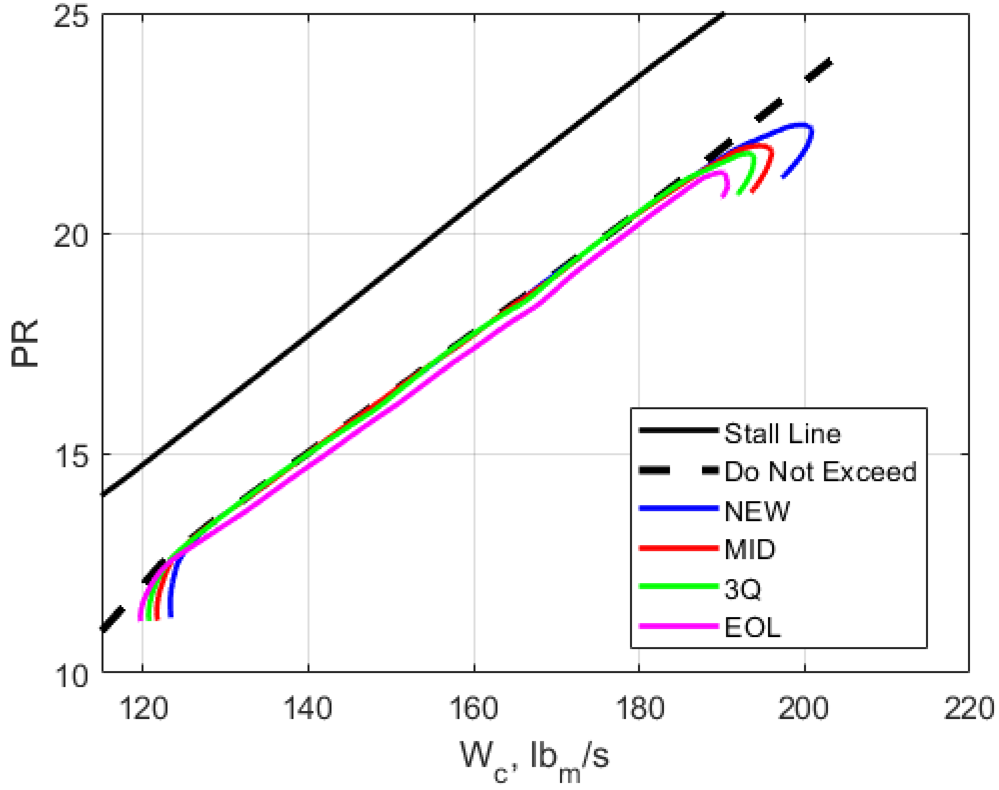


# The Engine Lifespan Optimization Approach

- Start at the conservative schedule and march toward the aggressive schedule
- Objective: minimize thrust response time while respecting compressor operability margin constraints
- Uses a Q-Learning algorithm
- Positive rewards for:
  - Reducing thrust response time
  - Increasing operability if the operability limit was violated with the prior action
- Negative rewards for:
  - Violating the operability constraint
  - Increasing the thrust response time while not violating the operability limit
  - Staying on the same schedule



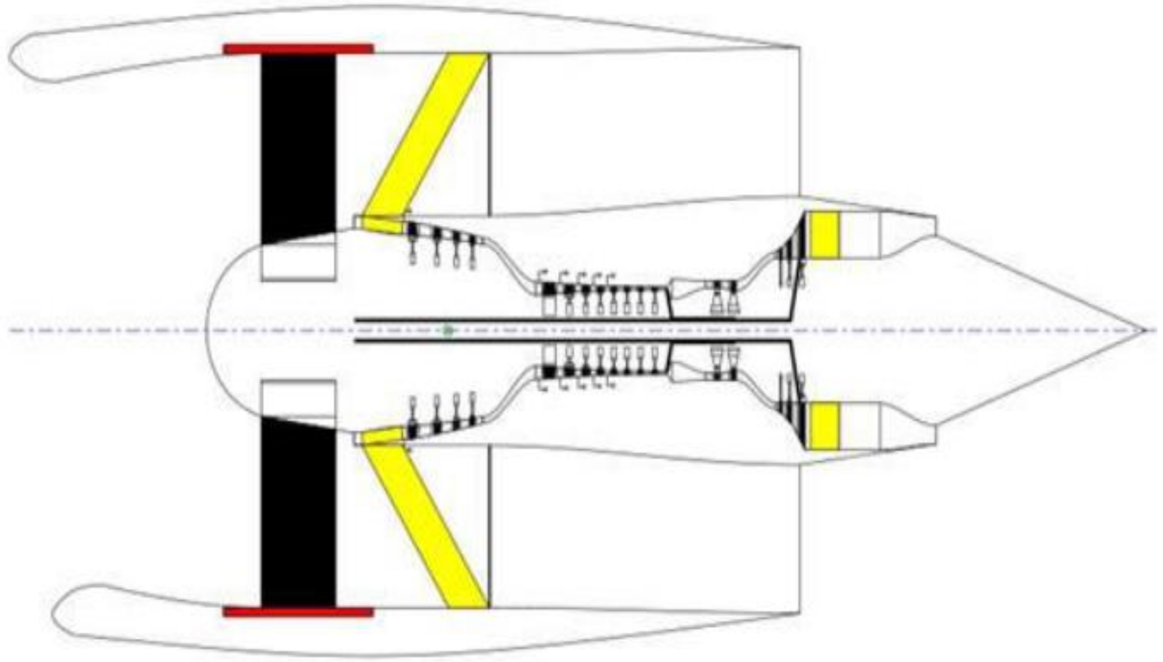

MID = Mid-life
3Q = 3-Quarter life

**Do Not Exceed Line was defined based on the EOL running line**

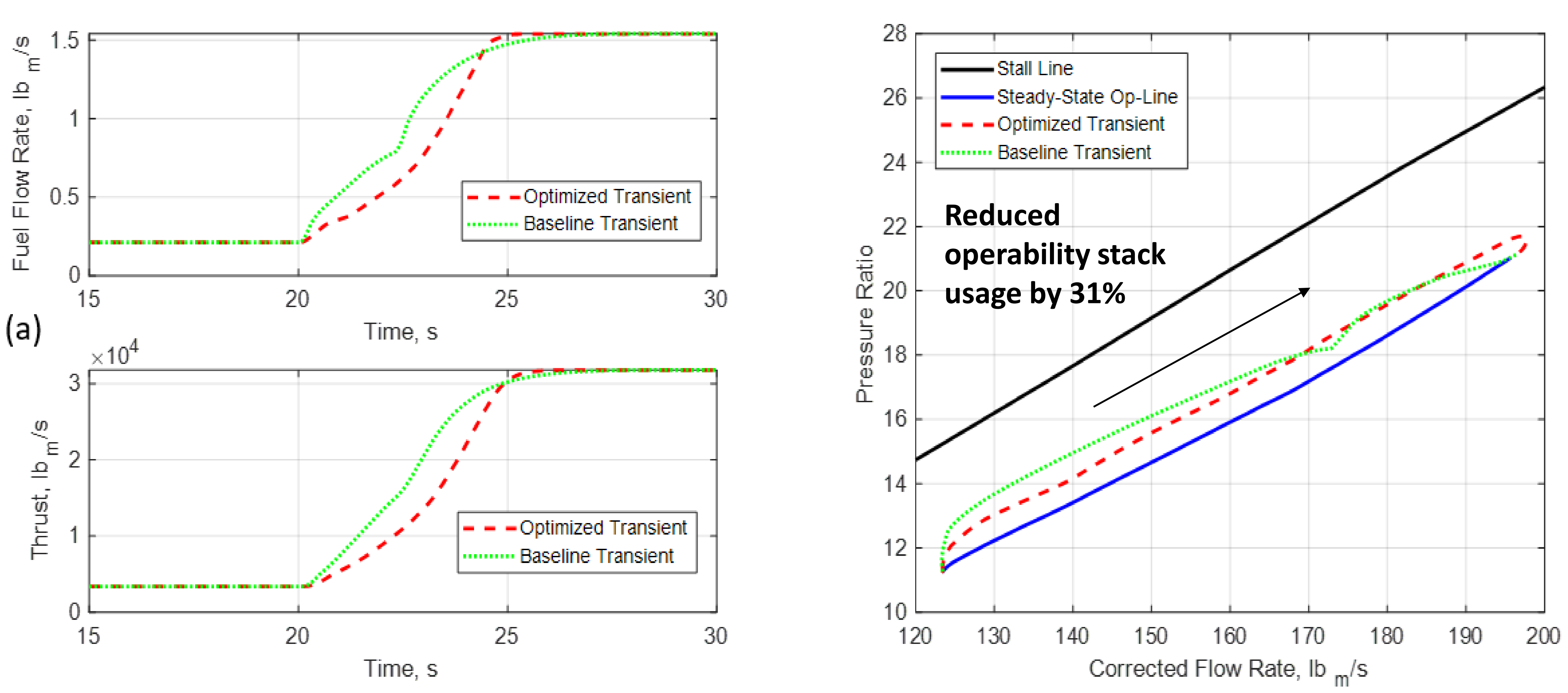
# Application - AGTF30 Engine

- Conceptual two-spool geared turbofan
- Produces ~30,000 $lb_f$ of thrust at sea level static (SLS) conditions
- Envisioned for single-aisle applications
- Included advanced technologies
  - Compact core
  - Variable area fan nozzle
- MATLAB/Simulink® model developed with the Toolbox for Modeling & Analysis of Thermodynamic Systems (T-MATS)
- Includes a baseline controller with representative performance
- Includes engine health parameters

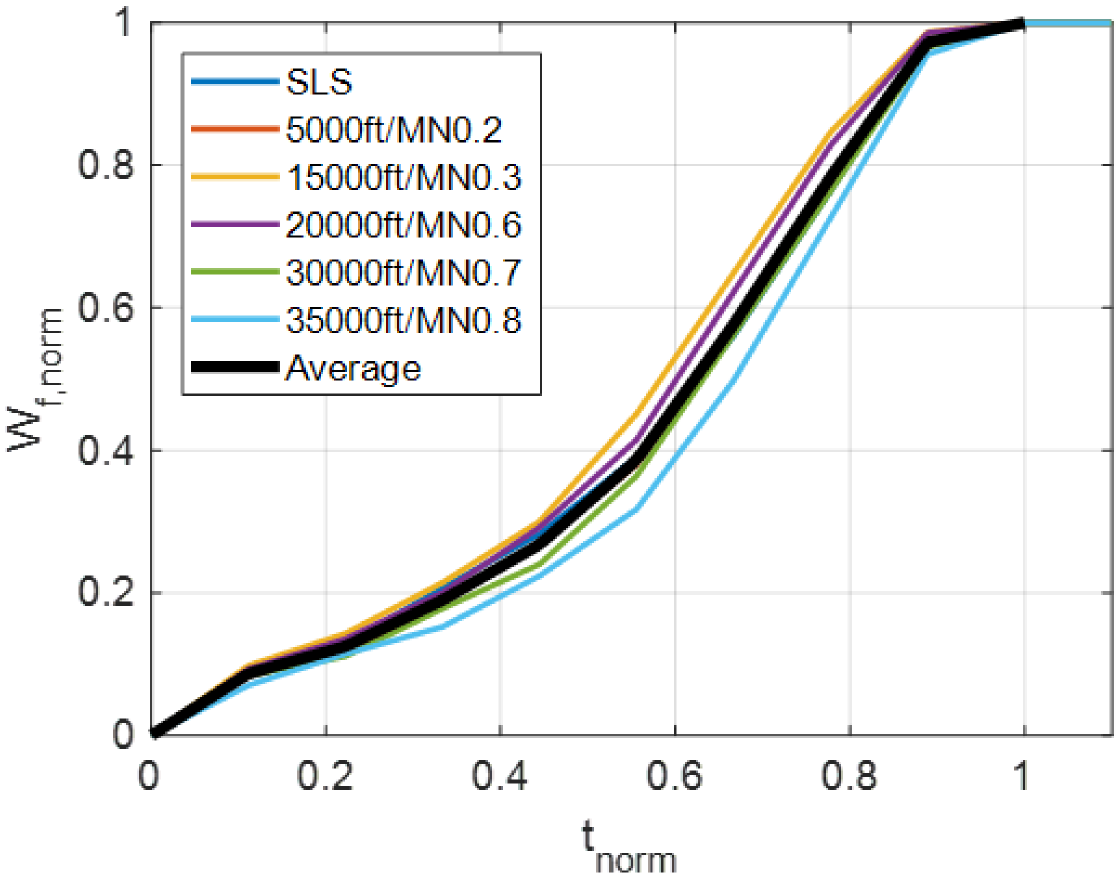
Advanced Geared Turbofan
30,000 $lb_f$ (AGTF30)

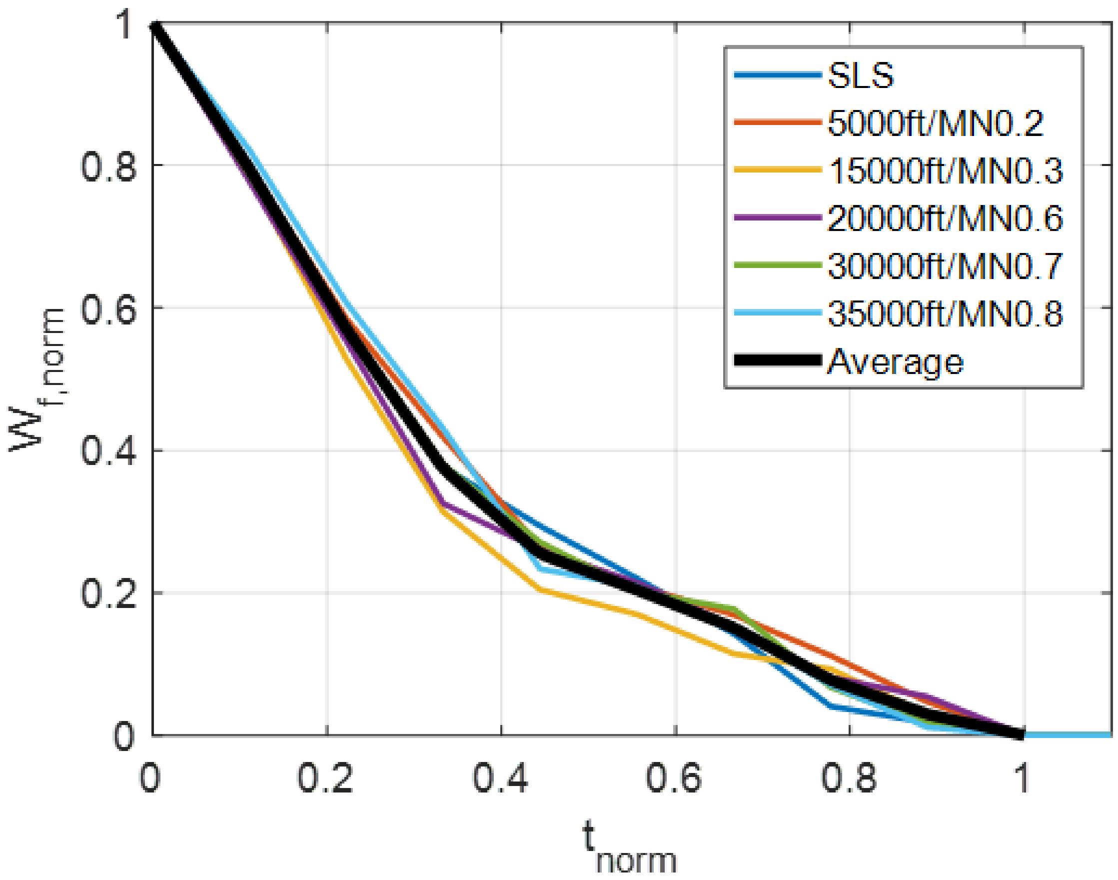


# Optimization Results - Acceleration



# Optimization Results – Generalize Profile



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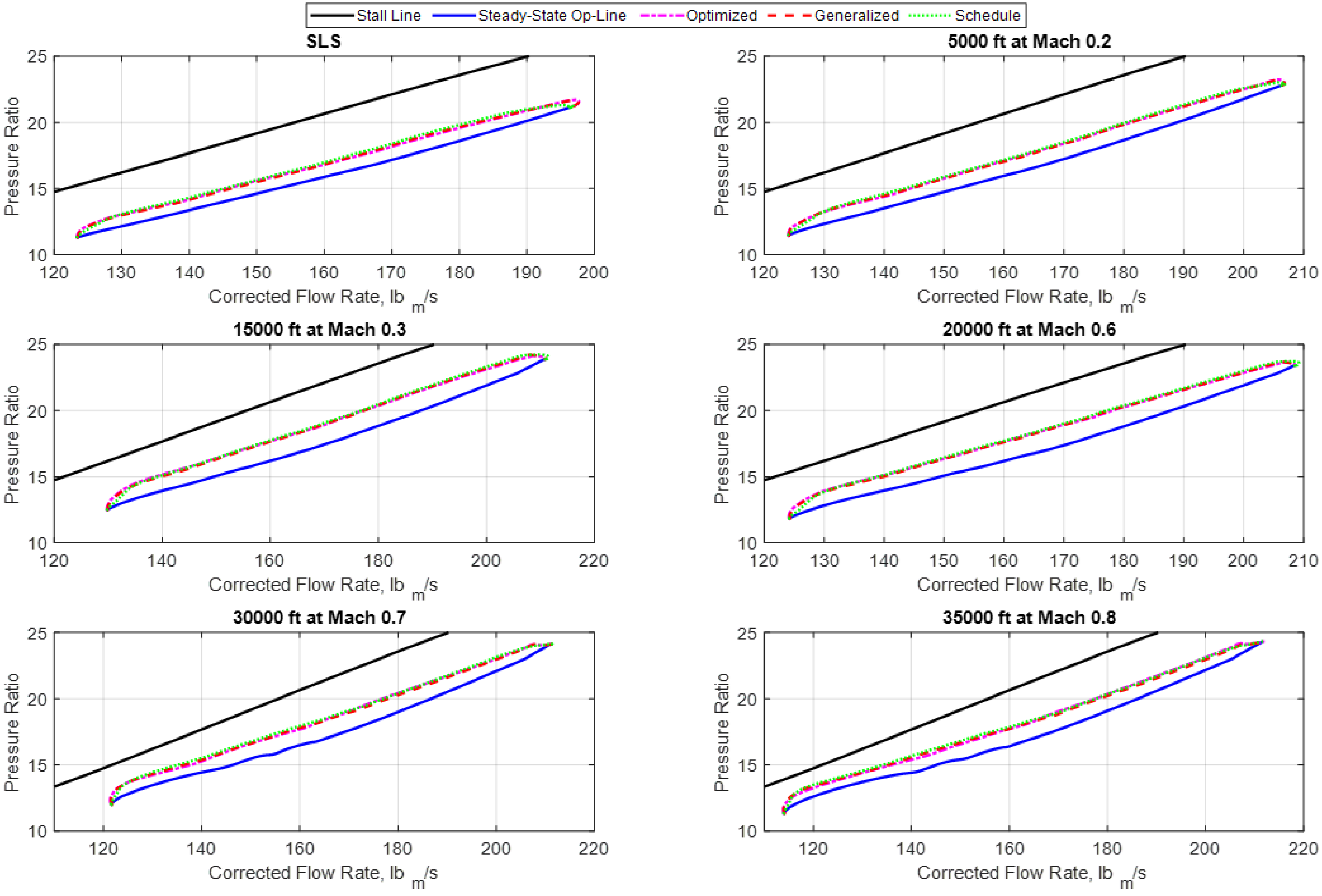
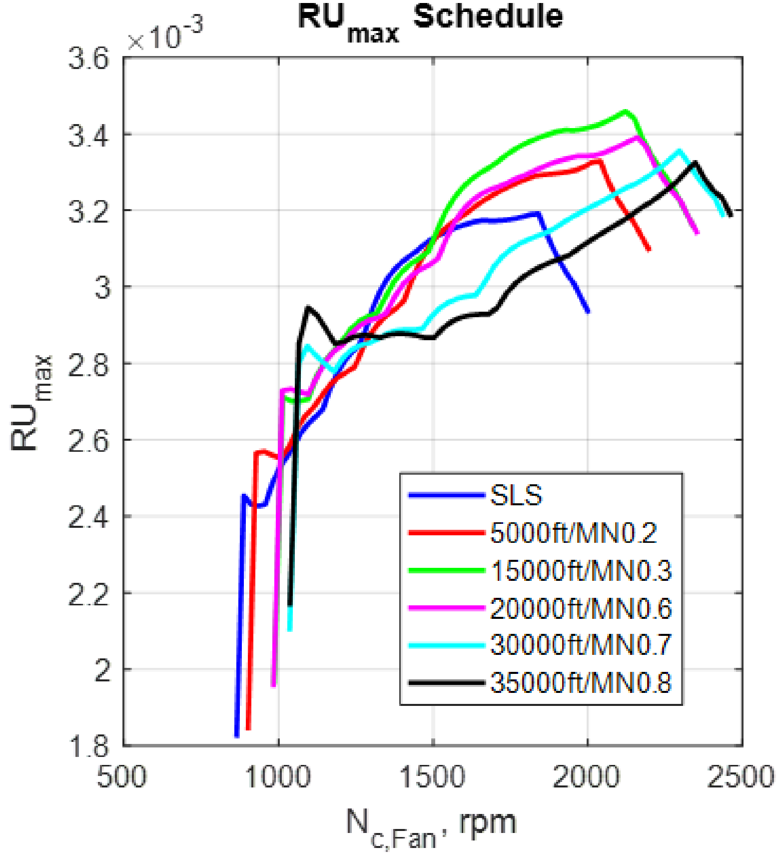
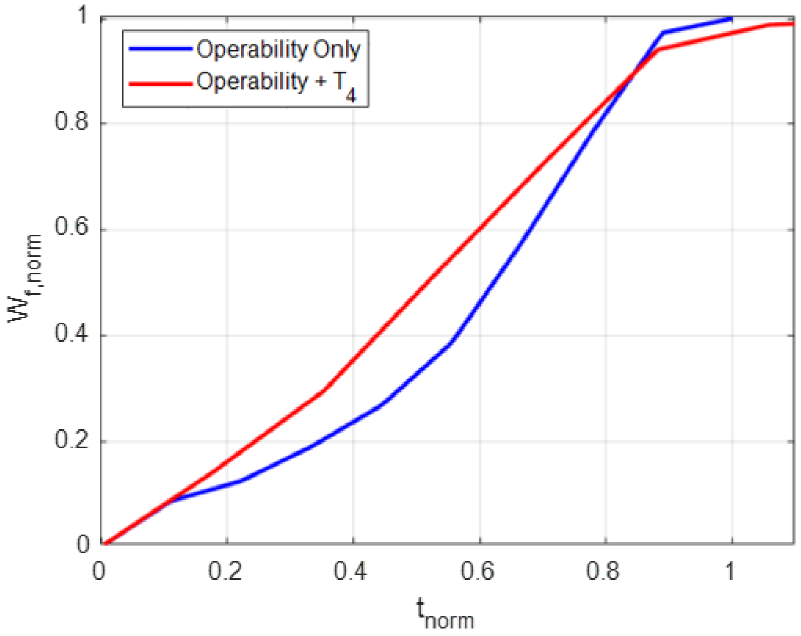
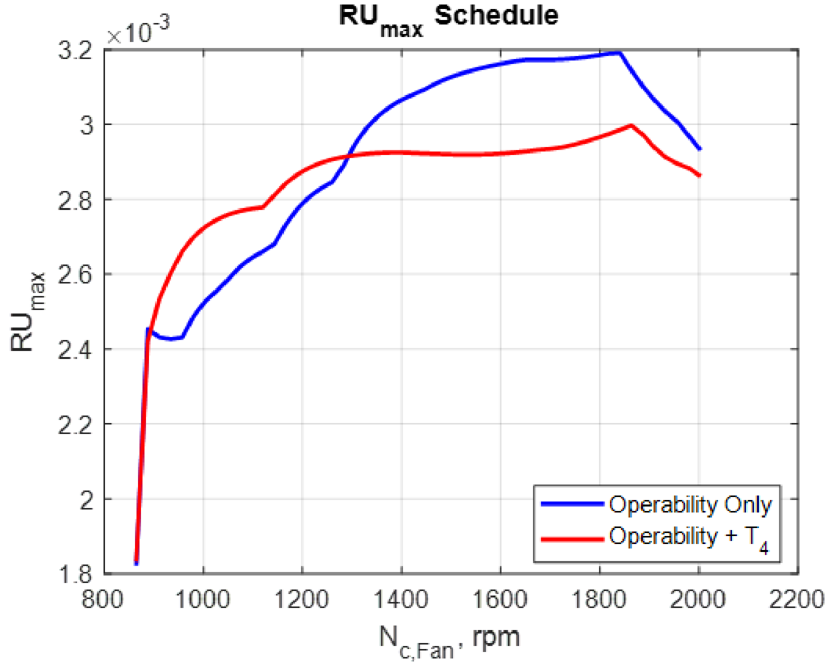


# Optimization Results – Life Extension Consideration



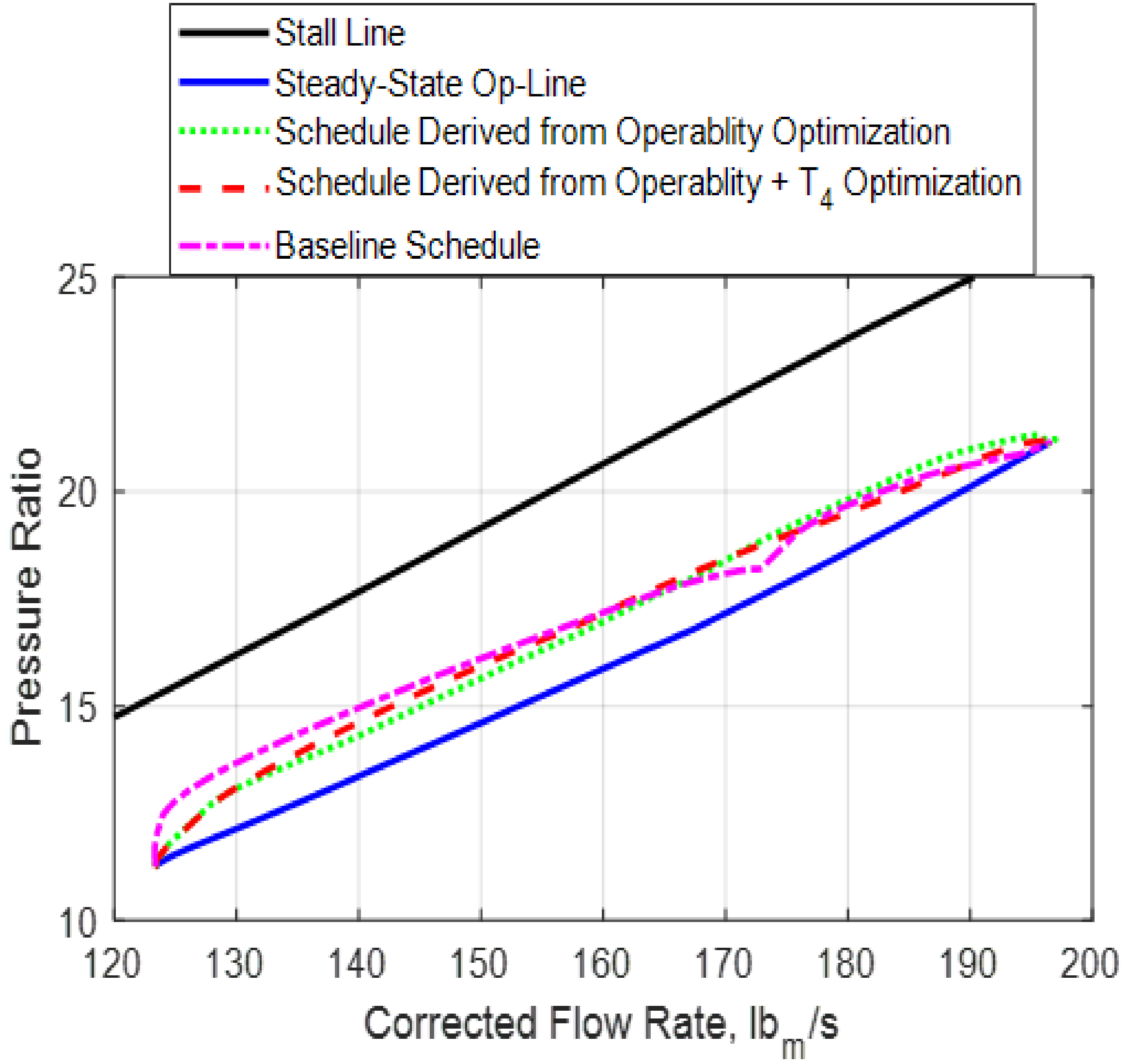




$$f = \frac{3}{TSU} + \frac{10}{\left(T_{4,peak} - T_{4,SS}\right)/T_{4,SS} + 1}$$

Peak Turbine Inlet Temperature

Steady State Turbine Inlet Temperature

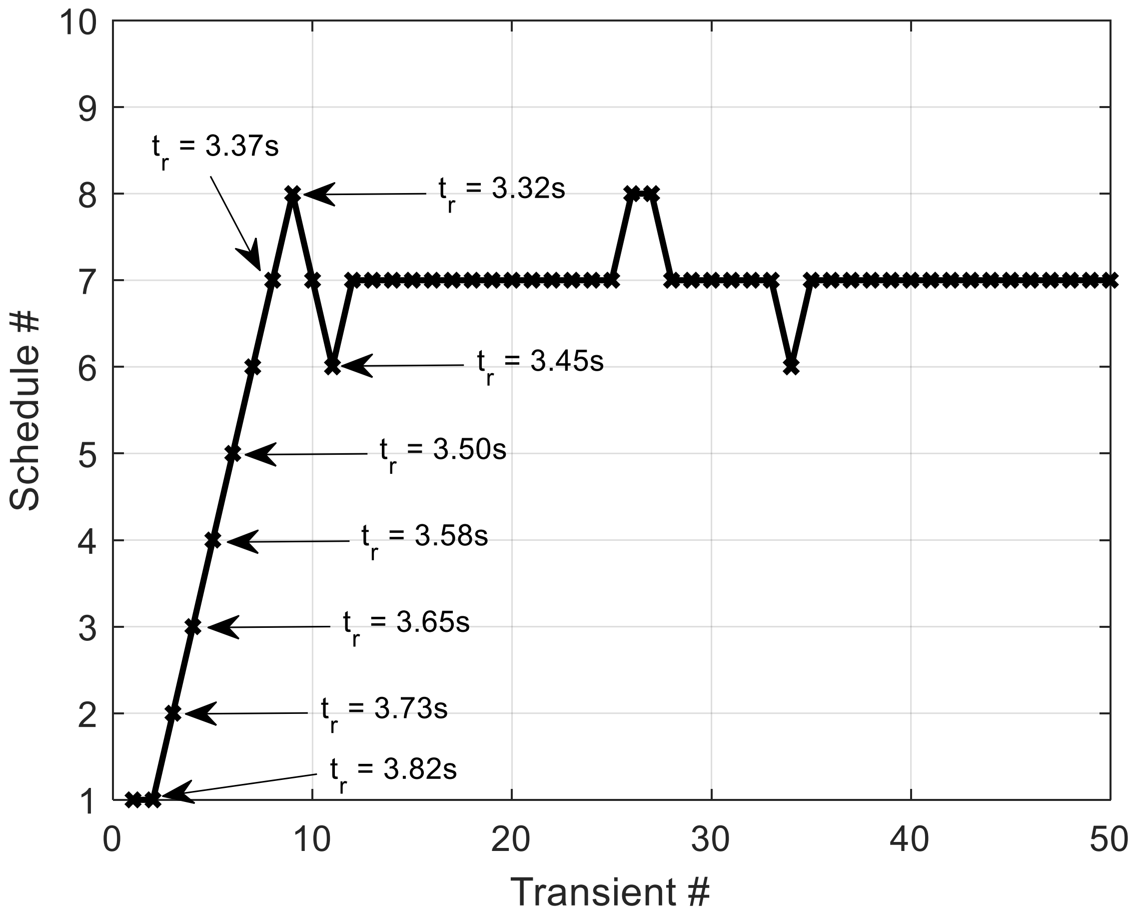
# Optimization Results – Life Extension Consideration

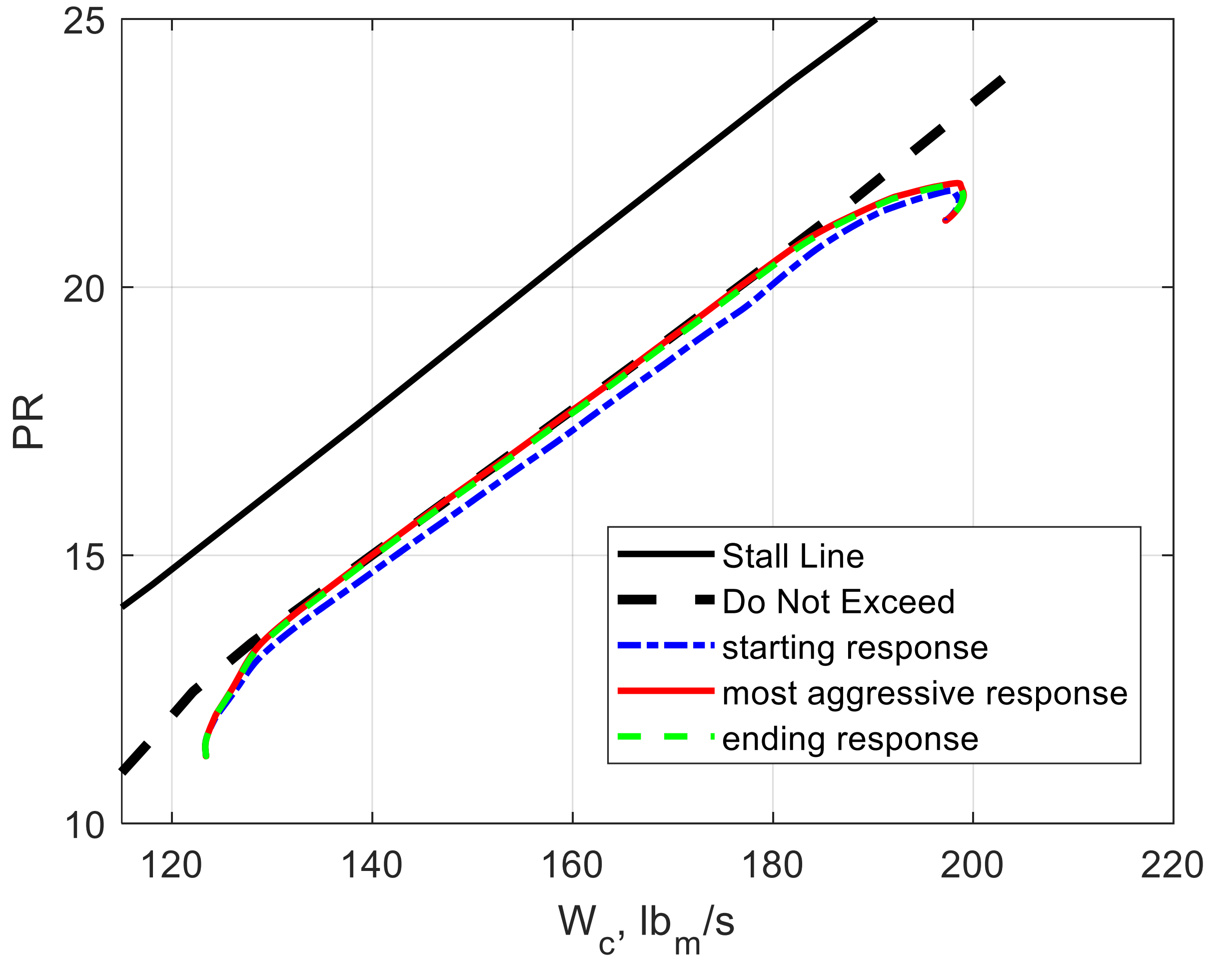



| Schedule | Full Power Burst TSU, % | Derated Takeoff Burst Peak $T_4$, °R | Derated Takeoff Burst $T_4$ overshoot, % |
|---|---|---|---|
| Baseline | 38.4 | 2951 | 3 |
| Optimized Operability | 25.8 | 2989 | 4.3 |
| Optimized Operability + $T_4$ | 29.76 | 2972 | 3.7 |

# Engine Lifespan Optimization Results

## New Engine Training

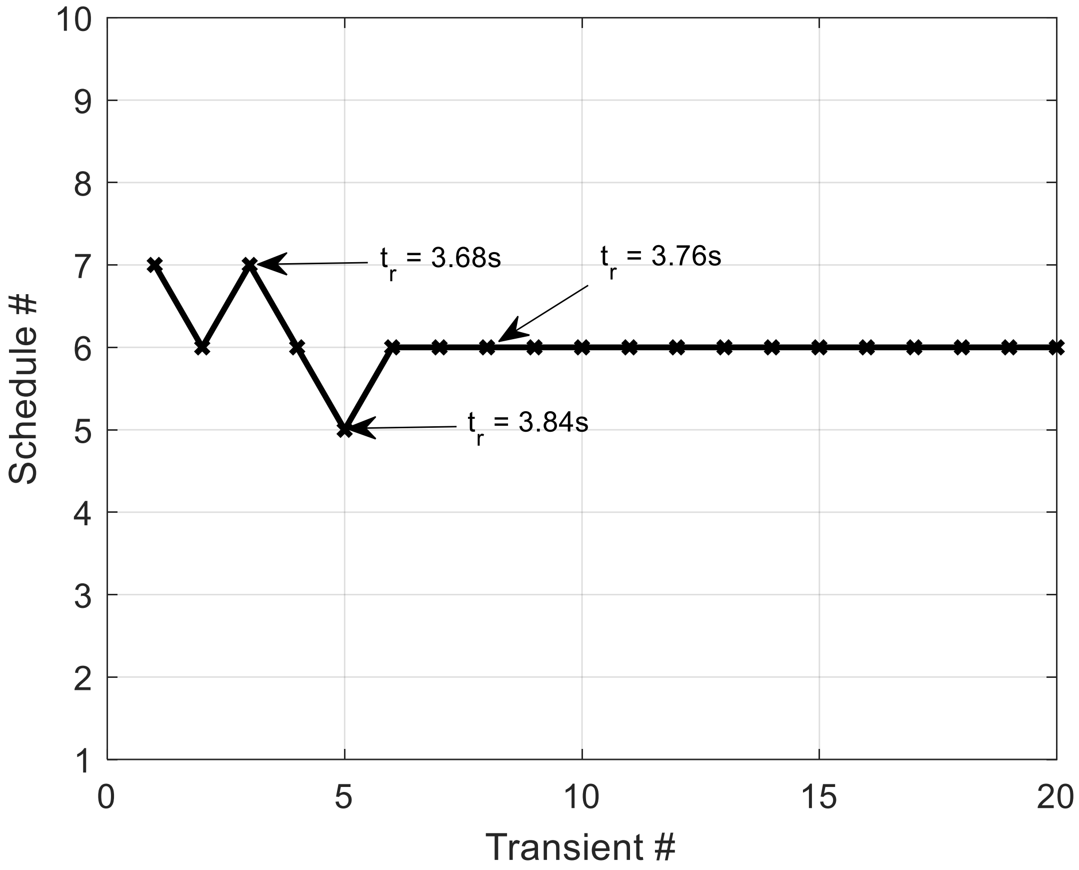



Reduced thrust response time by nearly 0.5s or 11.8%

# Engine Lifespan Optimization Results

- **Degraded the engine from new to mid-life to see how the RL agent would adjust**
- **RL adjusts to the engine degradation, demonstrating adaptability**



# Conclusions

- A genetic algorithm has been applied to optimize transient limit logic for a turbofan engine
  - Reduced the use of the overall operability stack by 31% compared to a baseline controller
  - Demonstrated success with generalizing optimization results across a wide range of flight conditions
  - Demonstrated how the approach can be modified to optimize for different goals (ex. reduced peak temperatures to preserve engine life)
- A reinforcement learning (RL) algorithm was applied in an approach to adjust the transient limit logic of a turbofan engine over its lifespan
  - Demonstrated the ability reduce the thrust response time by 11.8% while respecting operability limits
  - Results suggest the need to update the “optimal” schedule as determined by the optimization approach in concert with a digital twin might be unnecessary, thus reducing the workload for implementation
- Potential directions for future work
  - Address challenges for practical implementation of the RL approach
  - Modify the goals of RL approach to be better aligned with commercial engine applications

# Acknowledgments

- Funded by the Transformational Tools & Technologies (TTT) project under the Aeronautics Research Mission Directorate (ARMD)

# Questions/Discussion

Contact Information

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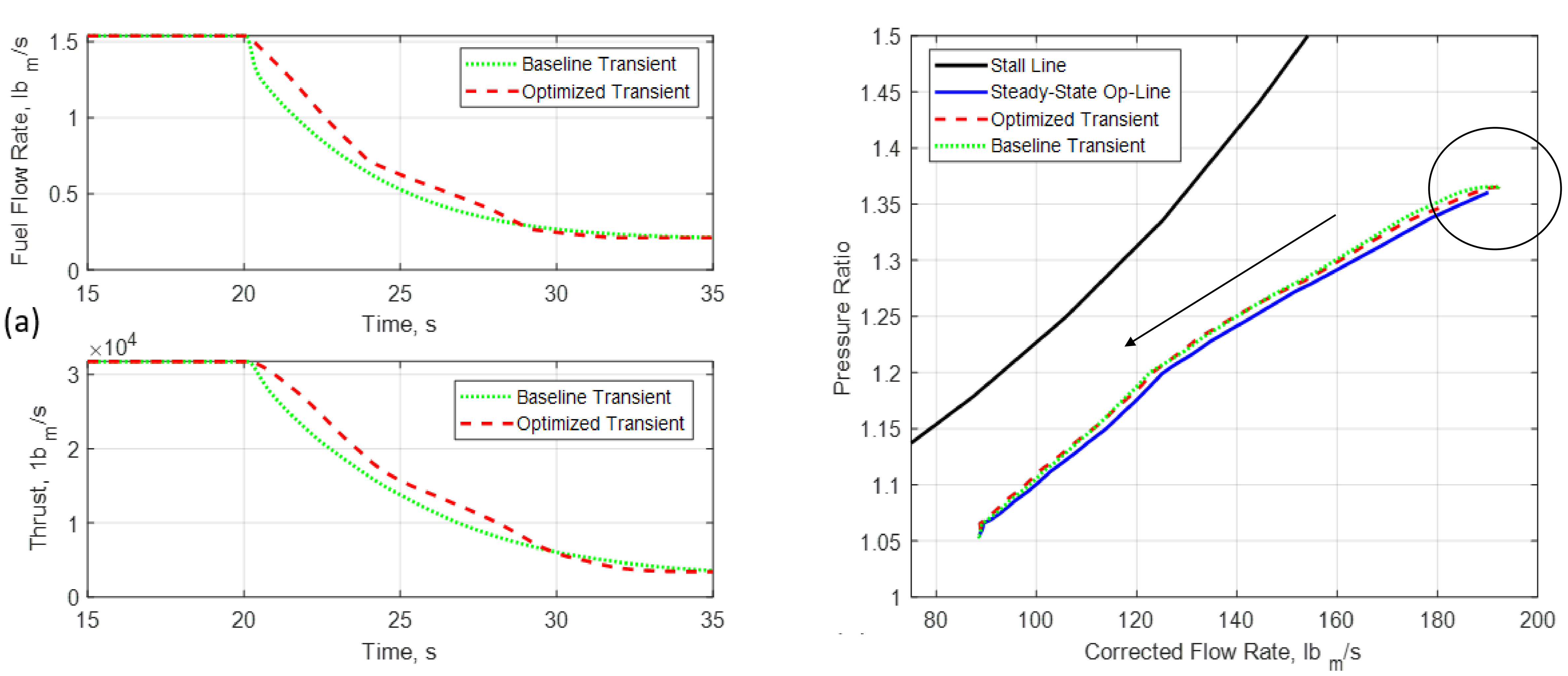
# Extra Charts

# Objectives

- Apply optimization techniques to optimize fuel flow control transient* limit logic for a turbofan engine to maximize operability to enable better performance
- Evaluate the optimized solutions against a baseline
- Leverage the optimization results and sensor feedback to guide a machine learning algorithm to modify the transient limit logic in order to achieve the best performance on the real system

* Transient refers to a change in engine power/thrust demand associated with acceleration or deceleration of the engine shafts.

# Optimization Results - Deceleration



# Optimization Results – Generalized Profile