



# Transient Optimization of a Gas Turbine Engine

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# 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.





# Contents and Organization

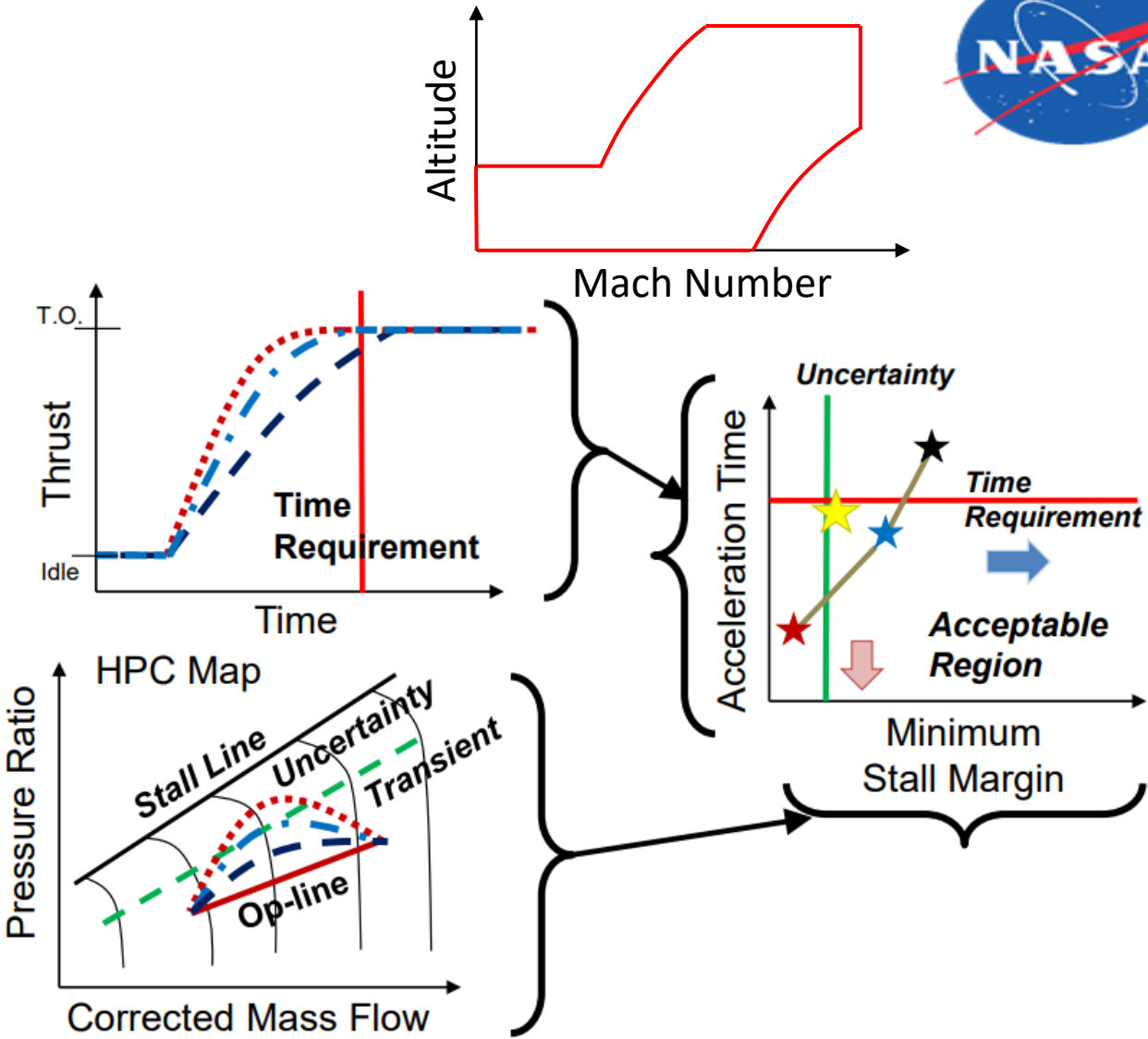
- Background
- Description of the Approach
  - Transient limit logic optimization
  - Optimization over the lifespan of the engine
- Application for Illustrating the Approach
- Transient Optimization Results (Abbreviated For Video Presentation)
- Engine Lifespan Optimization Results
- Conclusions





# 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<sup>†</sup>
  - 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



<sup>†</sup>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

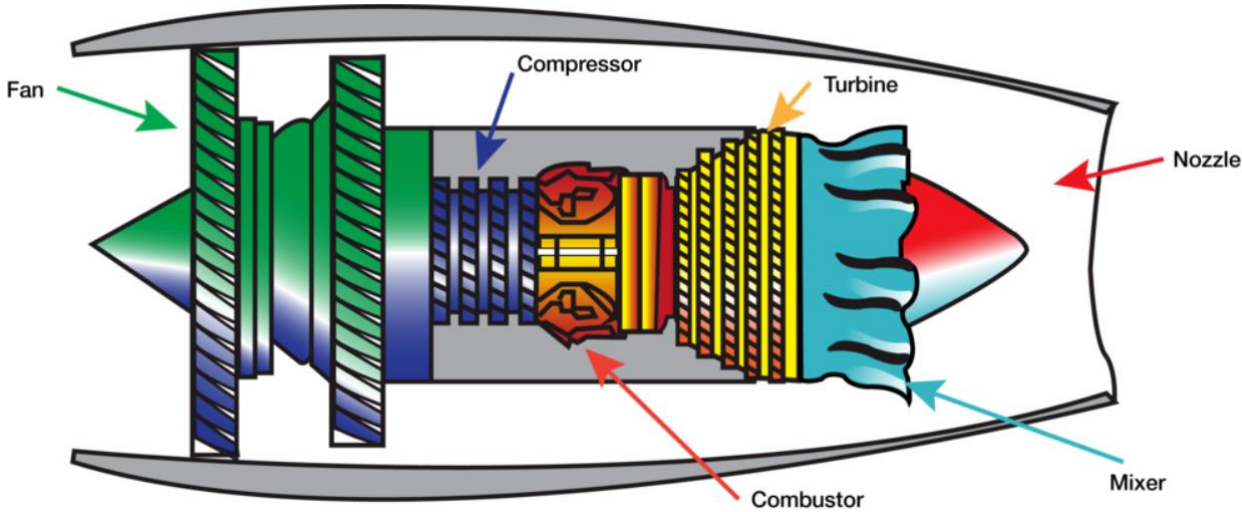


Image Credit: NASA

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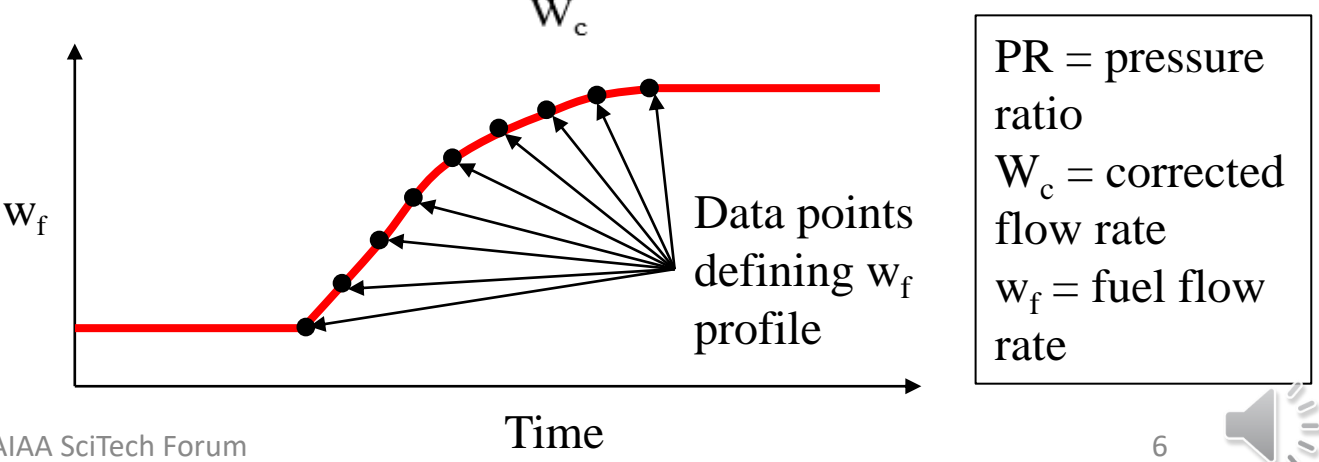
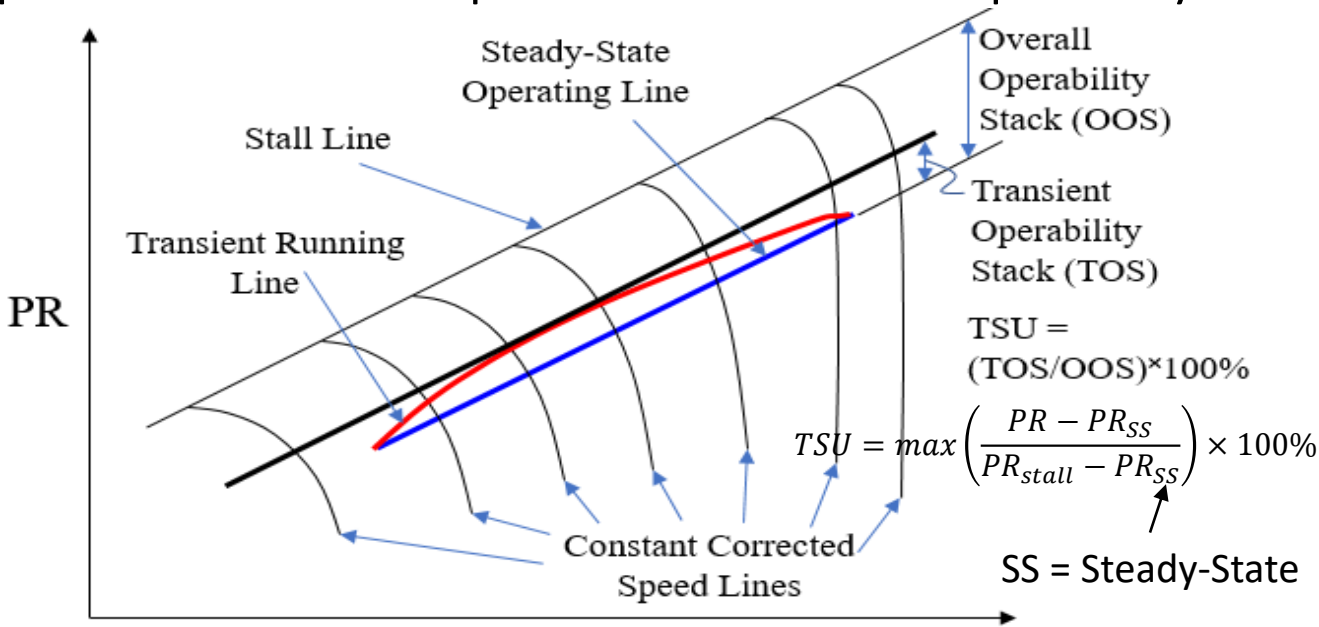
## DIGITAL REPRESENTATION





# The Optimization Approach

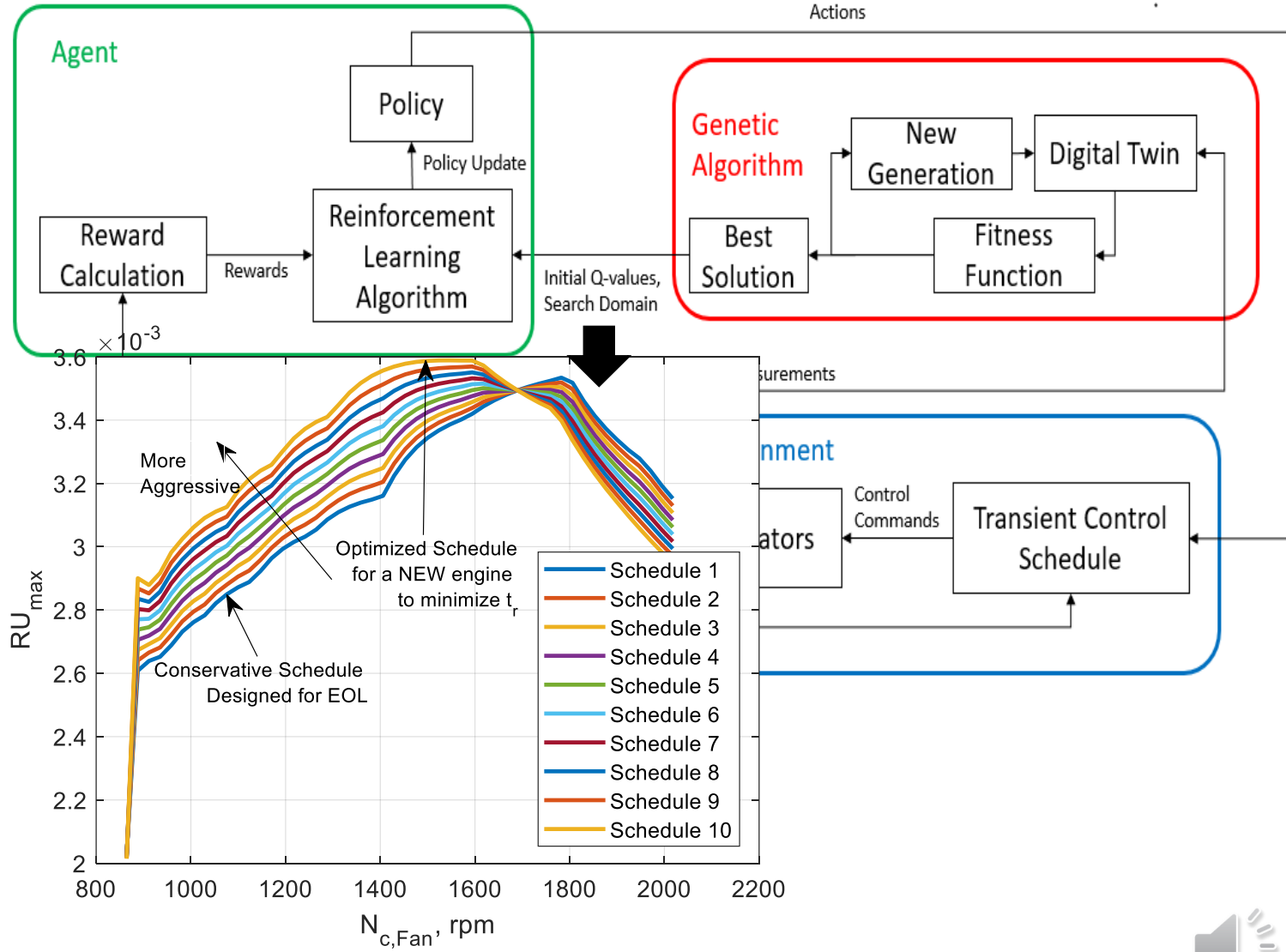
- A genetic algorithm is applied to identify the “optimal” fuel flow rate profile that maximizes operability as defined by the transient stack usage (TSU)
  - applies functions of elitism, carry-over (replication), cross-over (reproduction), and immigration
  - utilizes rank-based selection with probabilities 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





# The Engine Lifespan Optimization Approach

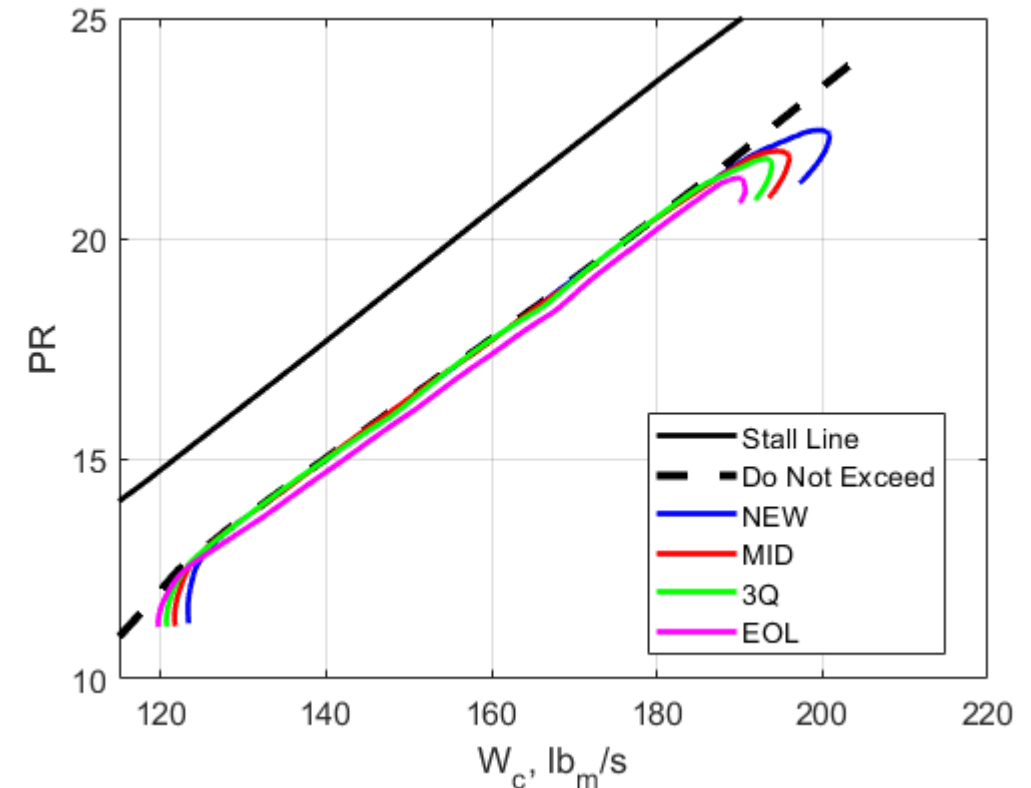
- Use the digital twin to
  - Design a conservative schedule for an end-of-life (EOL) engine
  - Design an aggressive schedule for a new (NEW) engine
  - Create an array of discrete schedules between the two extremes
  - Could update the “aggressive schedule” and discrete options over the lifespan of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





# 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

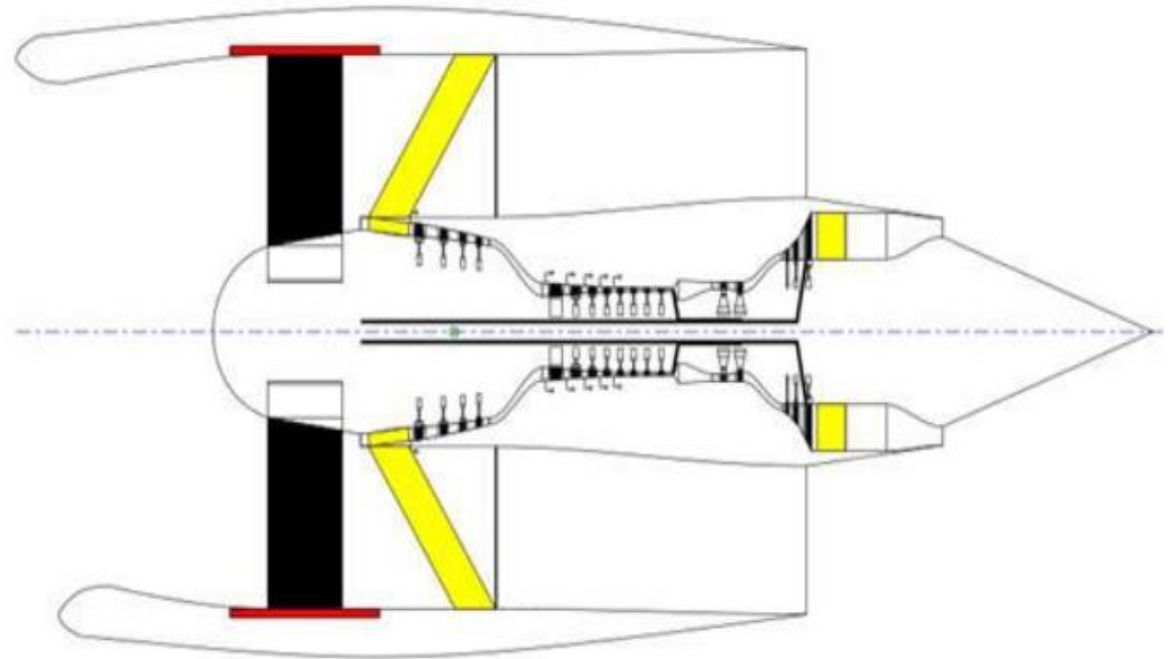
**Do Not Exceed Line was defined  
based on the EOL running line**



## Application - AGTF30 Engine

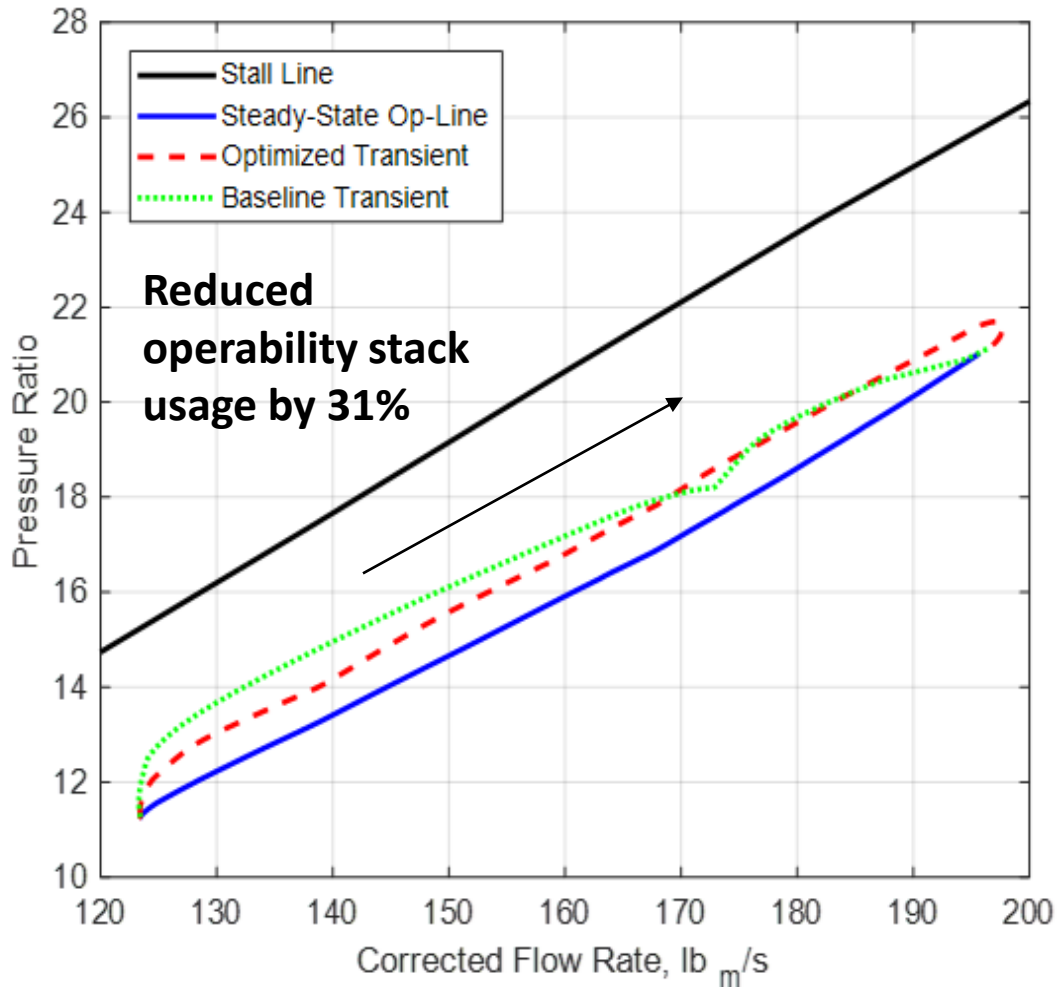
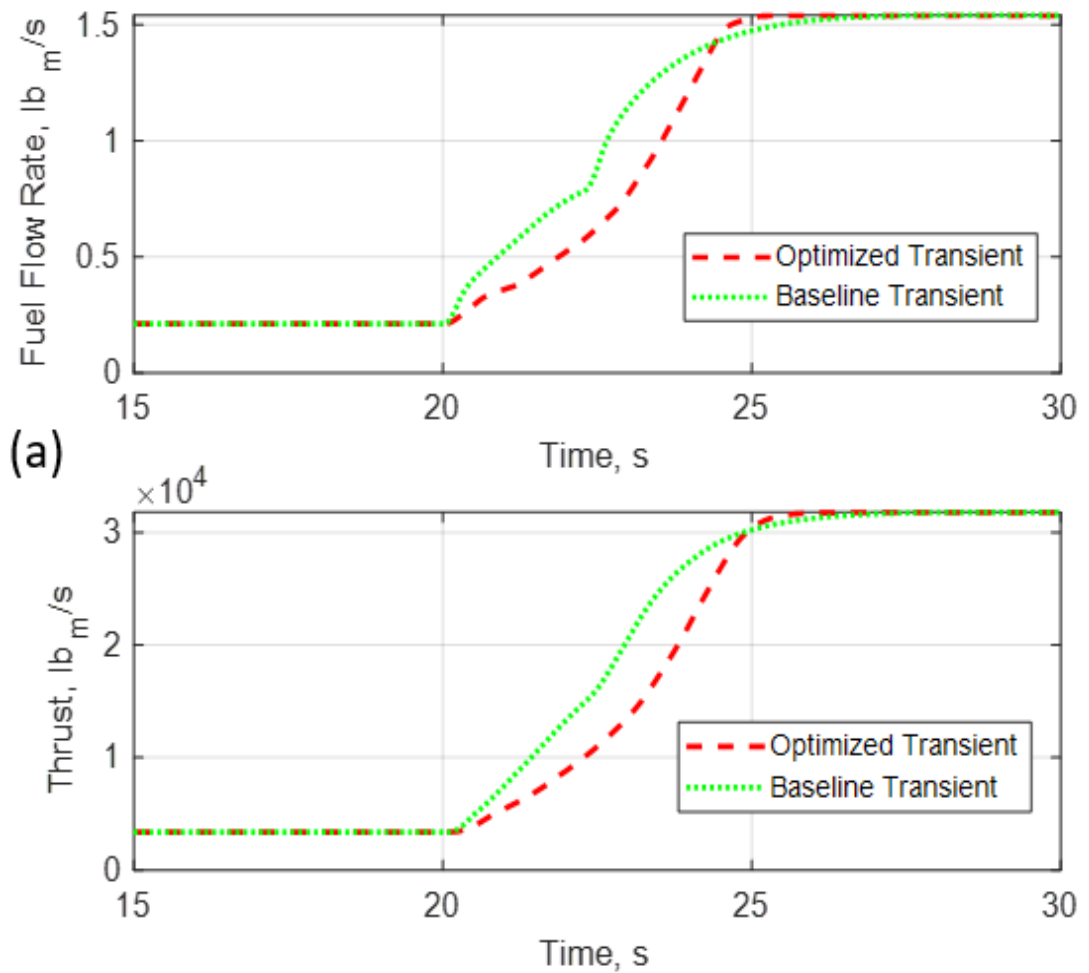
- Conceptual two-spool geared turbofan
- Produces  $\sim 30,000 \text{ lb}_f$  of thrust at sea level static (SLS) conditions
- Envisioned for single-aisle applications
- Included advanced technologies
  - Compact core
  - Variable area fan nozzle
- MATLAB/Simulink<sup>®</sup> model developed with the 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 $\text{lb}_f$ (AGTF30)





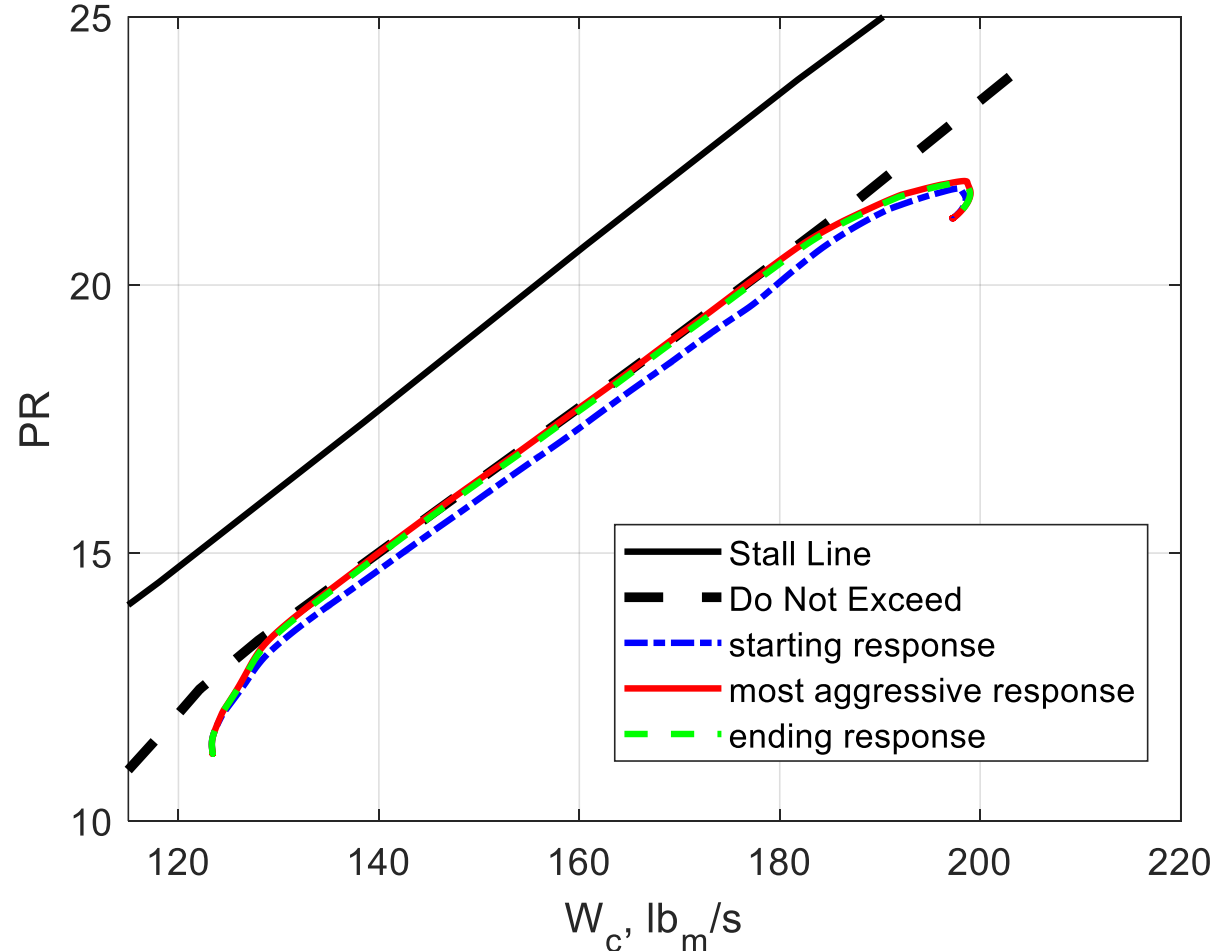
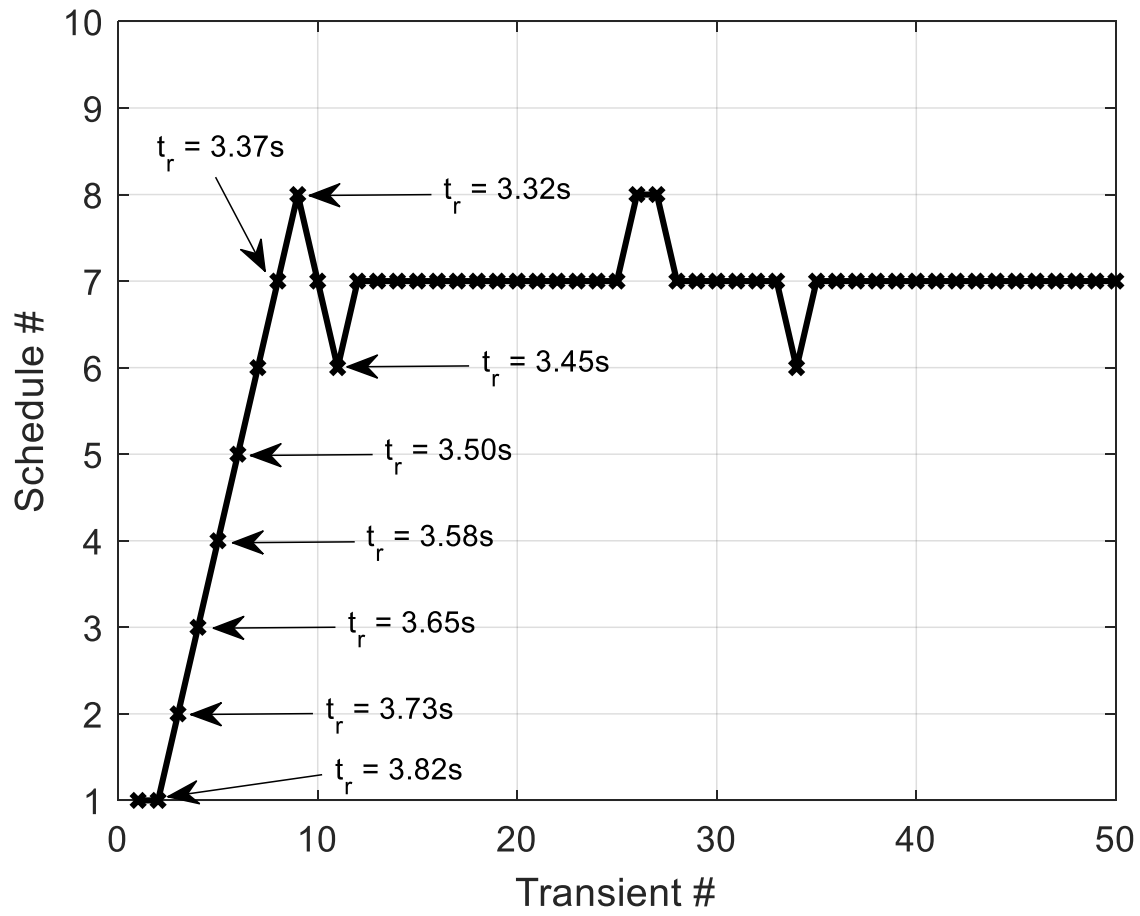
# Optimization Results - Acceleration





# Engine Lifespan Optimization Results

## New Engine Training



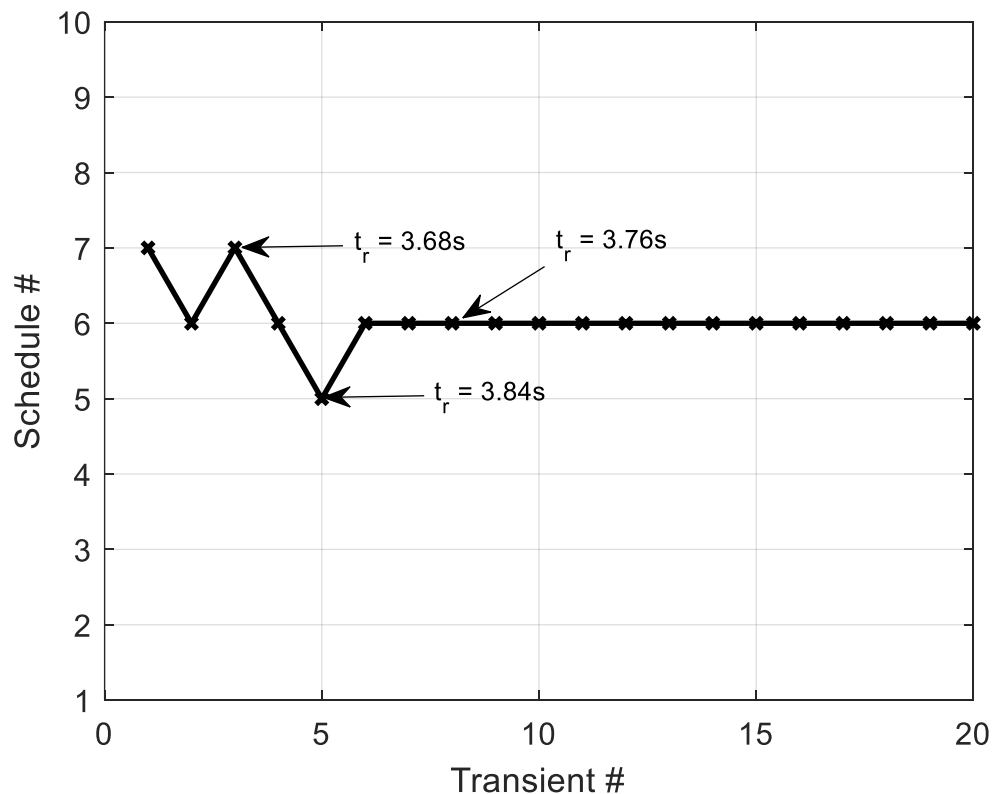
Reduced thrust response time by nearly 0.5s or 11.8%





# Engine Lifespan Optimization Results

Degraded the engine from new to mid-life to see how the RL agent would adjust



- RL adjusts as the engine degrades
- Attempted to refine the schedules by updating the “optimized” aggressive schedule as the engine ages.
  - Only resulted in a 0.02s improvement
  - Updating the schedule options may not add enough benefit to be warranted





# 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

\* Results omitted to meet video time constraint





# Acknowledgments

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

# Questions/Discussion

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