AI–Enabled Multi-Mode Adaptive Logistics Planning System (M2ALPS) In Support of the Air Force Adaptive Basing Concept-of-Operations

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Agenda

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- Objective
- Methodology
- M2ALPS
- Optimization Model
- M2ALPS Tool Kit
- AI-Enabled M2ALPS
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Background

- Air Force shifting towards Adaptive Basing (AB) concept
- AB requires rapid, reliable transport from central Hub to satellite Bases
- Current manual, heuristic approaches used by Logistics Planners (LPs)
  - Existing methods use deterministic approach and lack to capture uncertain scenarios
- Sophisticated logistics planning needed for Course of Action (COA) development
  - COA specifies equipment, supplies, personnel assignments and vehicle movements
  - Constraints: vehicle availability, cargo capacity, performance, cargo attributes
  - Route options needed for clearance issues, weather, vehicle limitations, no-fly zones

Objective

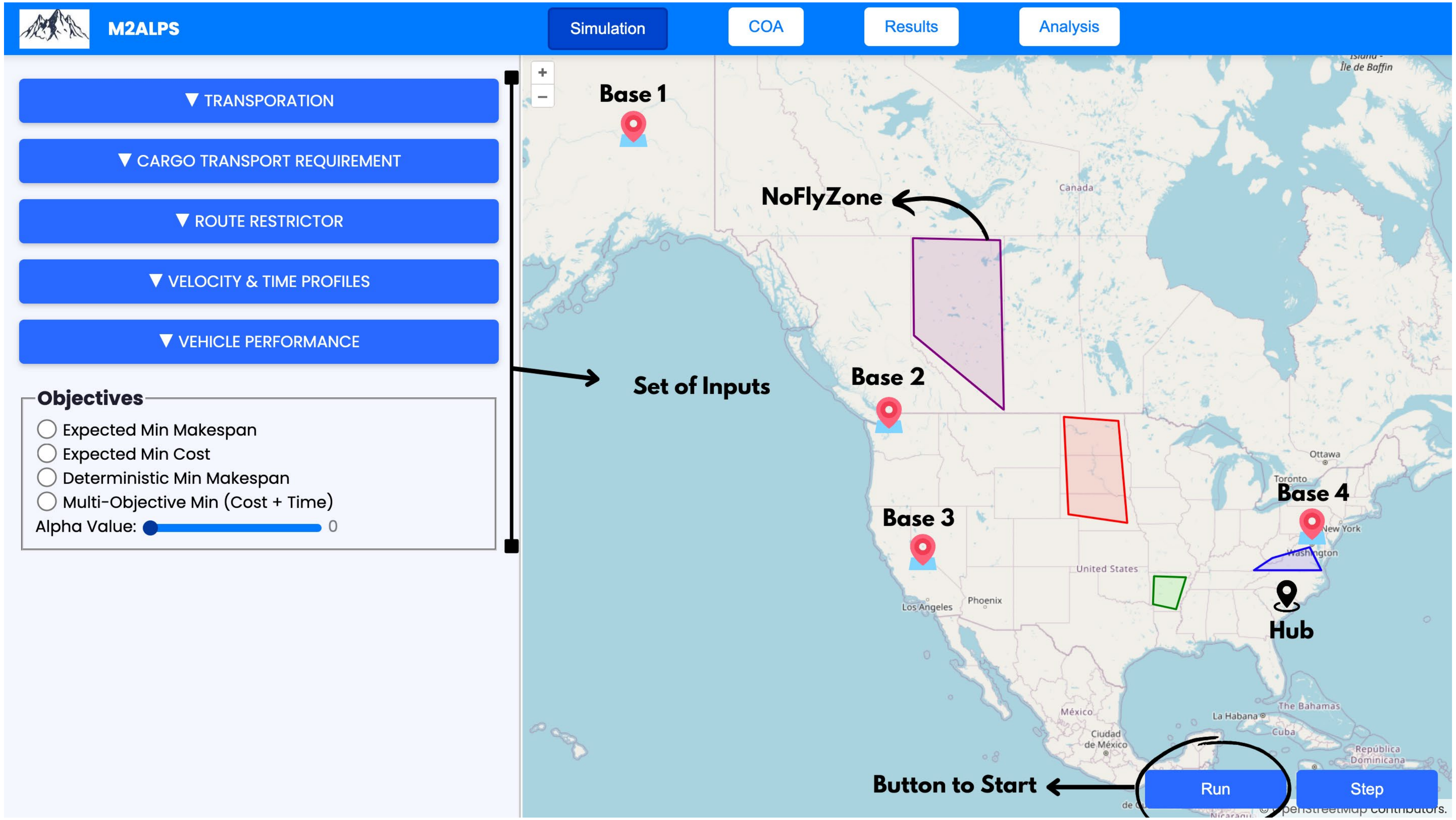
- To leverage a framework that combines simulation and optimization techniques for multi-mode logistics planning in military environments
- Incorporate risk factors and uncertainties into the logistics planning process for enhanced resilience and robustness
- Address the hierarchical nature of logistics decision-making that captures strategic and tactical decisions
- Demonstrate the effectiveness of the proposed framework through a case study and discuss its implications for military logistics decision-making

Multi-Mode Adaptive Logistics Planning System (M2ALPS) - Methodology

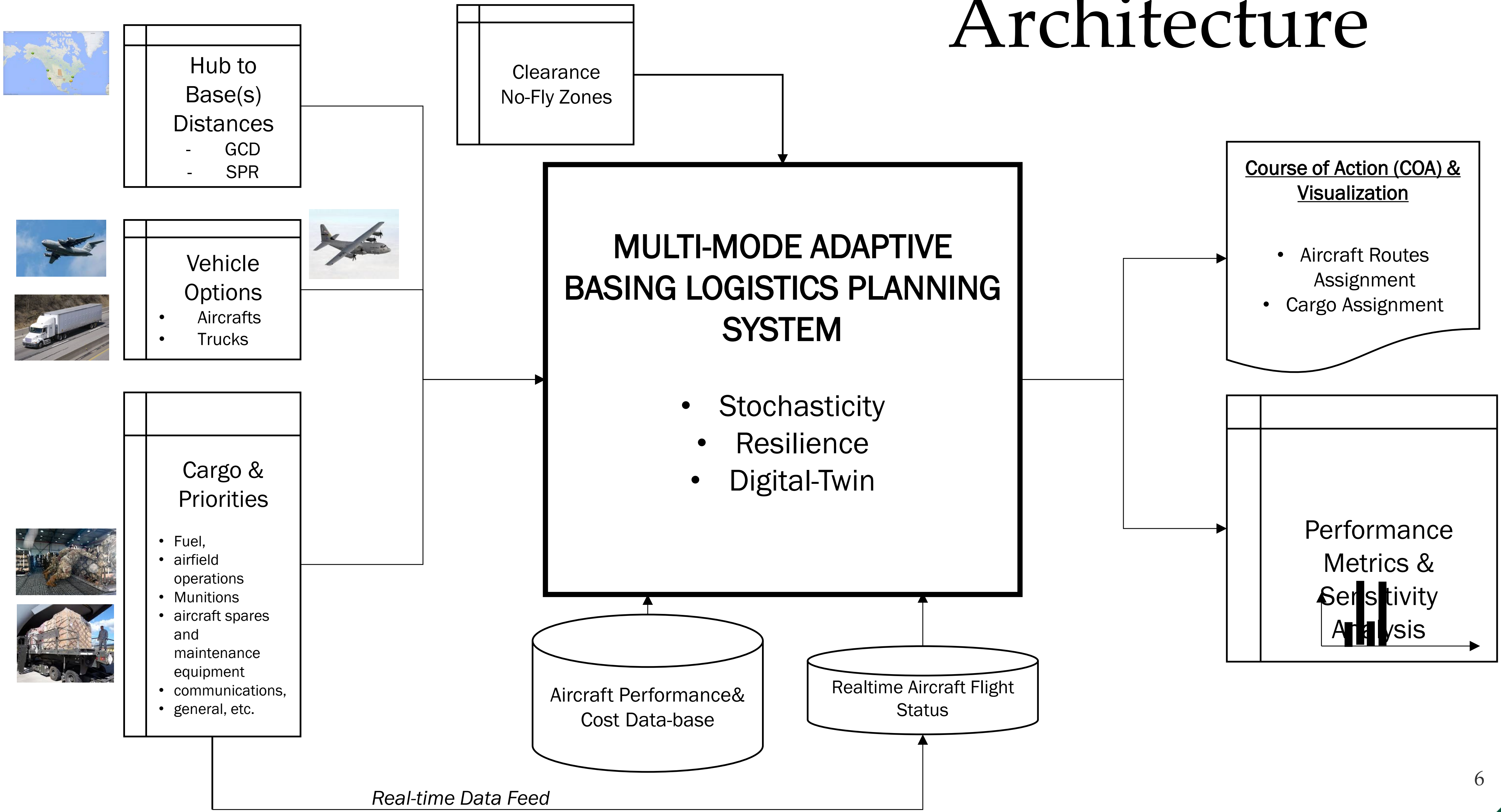
- **Simulation**:
  - Models air/ground networks linking supply to demand
  - Simulates goods flow with vehicle and route constraints
  - Uses statistical distributions for speed/loading times
  - Incorporates no-fly zones and clearance processes

- **Stochastic Optimization**:
  - Generates resilient plans for worst-case scenarios
  - Manages fleet allocation for base demands
  - Considers vehicle, capacity, time, and clearance constraints
  - Minimizes delivery time, flight time, and cost
  - Objectives: effectiveness, efficiency, and multi-objective

Simulation Environment



Architecture



Optimization Model - Inputs

- **Transportation Modes**: Air vehicles categorized as VL (Very Large) and L (Large) and Ground vehicles categorized as T (Trucks).
- **Vehicles**: A list of available air and ground vehicles.
- **Bases**: The destinations (jobs) requiring deliveries.
- **Demands**: Quantities of goods to be delivered to each base.
- **Priorities**: Priorities of goods to be delivered to each base.
- **Load/Unload Times**: Stochastic load and unload times for each type of vehicle.
- **Speed of Vehicles**: Different speeds for vehicles during loading and unloading.
- **Clearance Status**: Conditions that might affect travel distances to destinations.
- **Vehicle Availability**: Availability of each vehicle for scheduling.
- **Vehicle Capacity**: Maximum capacity of each type of vehicle.

Base Location	Great Circle Distance from Hub (nautical miles)	Shortest Path Distance from Hub (miles)
D1	5821	4485
D2	3919	2937
D3	3572	2481
D4	716	529

Table 1: Distance Matrix – Input Data

Optimization Model – Parameters

- C_i: Capacity of vehicle i
- N_i: Number of crew members for vehicle i
- $Q_{j,k}$: Quantity of job j of type k to be delivered
- P_k: Priority of order type k (lower value indicates higher priority)
- L_i: Nominal load/unload time of vehicle i
- V_i: Nominal travel speed of vehicle i
- $D_{i,j}$: Distance from vehicle i to hub j
- ΔL_i: Maximum deviation in load/unload time of vehicle i
- ΔV_i: Maximum deviation in travel speed of vehicle i
- F_i: Nominal fuel consumption rate for vehicle i (in gallons per hour)
- ΔF_i: Maximum deviation in fuel consumption rate for vehicle i (in gallons per hour)
- C_f: Cost of fuel (in dollars per gallon)
- C_l: Labor cost (in dollars per hour)
- $\mathrm{Pr}_{i,s}$: Probability of vehicle i being unavailable in shift s ($0 \leq \mathrm{Pr}_{i,s} \leq 1$)
- A_i: Binary parameter indicating if vehicle i is available (1 if available, 0 if not)
- α, β: Weights for the objective function terms
- Min_Util: Minimum utilization threshold for vehicles
- Max_Gap: Maximum allowed gap between consecutive shifts (set to 2 time units)

Worst – Case – Optimization:

- Mitigating Uncertainty: Ensures transportation plans withstand uncertainties in vehicle performance and external disruptions.
- Decision-Making Resilience: Provides reliable logistics under worst-case scenarios, optimizing costs and timelines effectively.

NTE: Not to Exceed Time Constraint – Parameter for Worst Case

Total Processing Time for each Trip – All Vehicles

Calculate the worst-case processing time for each trip, including loading, travel, and unloading times.

$$P_{i,j,s} = (L_i + \Delta L_i) + \frac{D_{i,j}}{V_i - \Delta V_i} + (L_i + \Delta L_i) \quad \forall i \in I, \forall j \in J, \forall s \in S$$

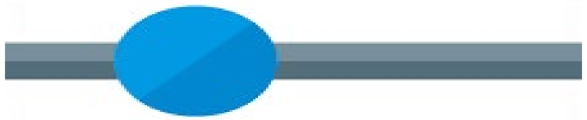
Optimization Model – Objective Function

- Cost Minimization (Efficiency)
- Make span Minimization (Effectiveness)
- Worst Case Optimization
- Multi-Objective Approach

$$\min Z = \alpha U + \beta Z \tag{1}$$

where:

- U represents the total completion time for all jobs.
- Z represents the total cost of the schedule.
- α and β are the weights for balancing the importance of completion time and cost, respectively.



Optimization Model – Constraints

- Job Quantity Assurance: Ensures full assignment of required job quantities across all vehicles and shifts.

$$\sum_{i \in I} \sum_{s \in S} X_{i,j,k,s} = Q_{j,k} \quad \forall j \in J, \forall k \in K$$

- Capacity and Availability Compliance: Restricts job assignments to vehicle capacities, adjusted for availability.

$$\sum_{j \in J} \sum_{k \in K} X_{i,j,k,s} \leq C_i \times A_{i,s} \quad \forall i \in I, \forall s \in S$$

- Sequential and Timely Execution: Maintains logical sequence and timing between shifts, limiting the gap to ensure continuity

Optimization Model – Constraints

- Priority Enforcement: Prioritizes higher importance jobs, scheduling and completing them before others

$$W_{j,k,s} \geq \frac{\sum_{s' \leq s} \sum_{i \in I} X_{i,j,k,s'}}{Q_{j,k}} \quad \forall j \in J, \forall k \in K, \forall s \in S$$

$$\sum_{s' \leq s} W_{j,k,s'} \geq \sum_{s' \leq s} W_{j,k',s'} \quad \forall j \in J, \forall s \in S, \forall k, k' \in K \text{ where } P_k < P_{k'}$$

- Robust Timing: Ensures total completion time remains within limits, even under worst-case scenarios.

$$\sum_{i \in I} \sum_{s \in S} (t_{i,s} + P_{i,j,s}) \leq \text{max\_allowed\_time}, \quad \forall i \in I, \forall j \in J, \forall s \in S$$

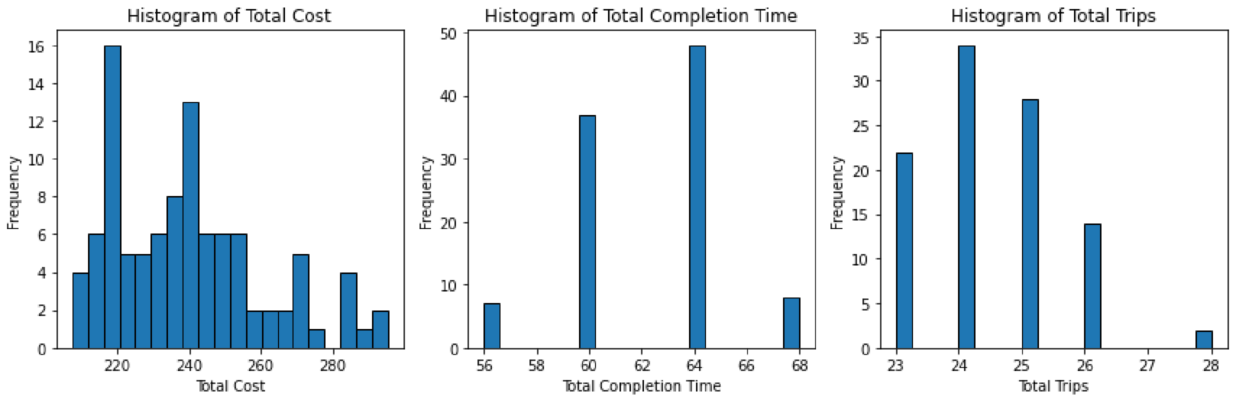
Sample Median Approximation Method

- Generates multiple worst case scenarios by sampling from the probability distributions of uncertain parameters (speed, load/unload times)

- Enhances model reliability by providing solutions that perform better under various worst-case scenarios

Case Study – Min Make Span – Effectiveness

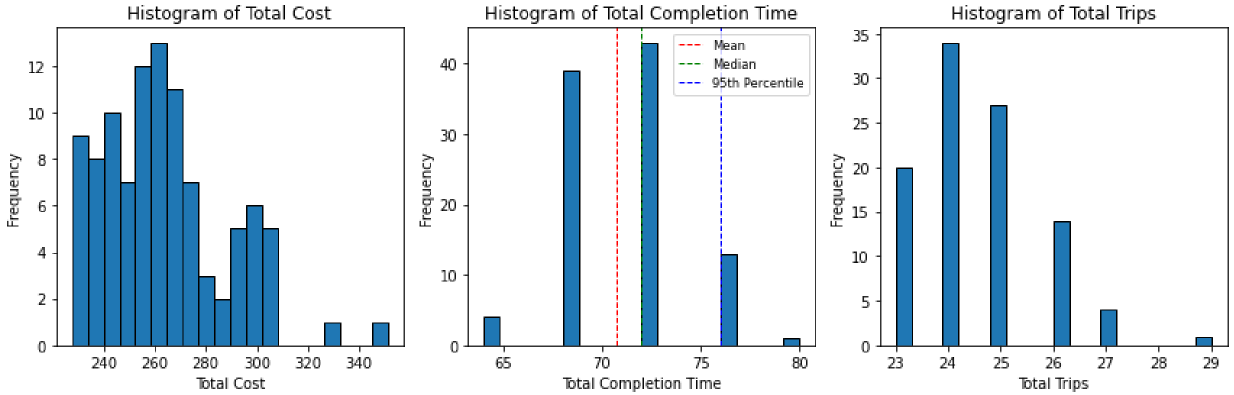
Under no Worst-Case Scenario



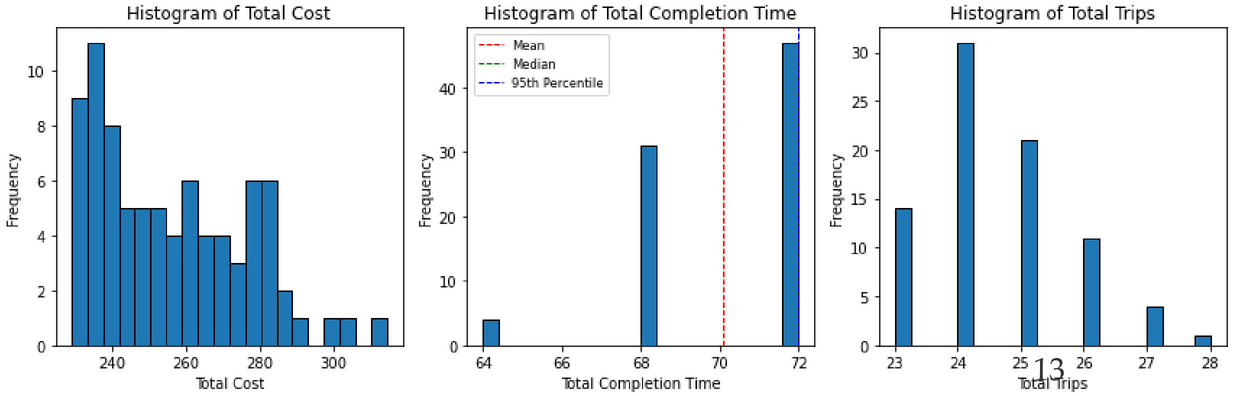
Max Acceptable 95th -%tile Worst Case – Constraint

- Parameterize the 95th Percentile Worst Case Completion Time
- Constraint the Model to ensure that the completion time does not exceed 75 hours

Under 10% Worst Case Scenarios

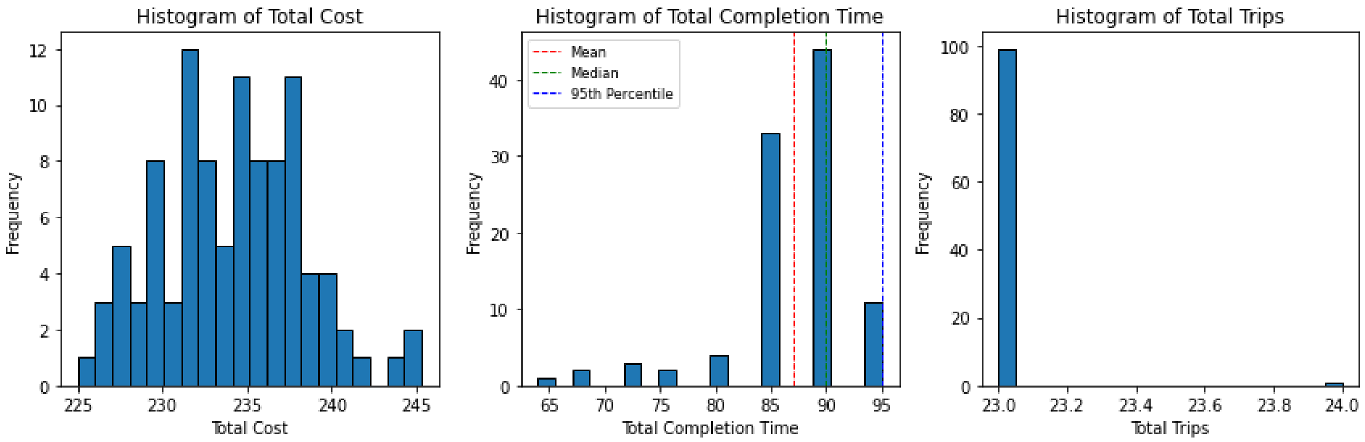


Under 10% Worst Case Scenarios & Max Acceptable 95th %-tile Worst-Case

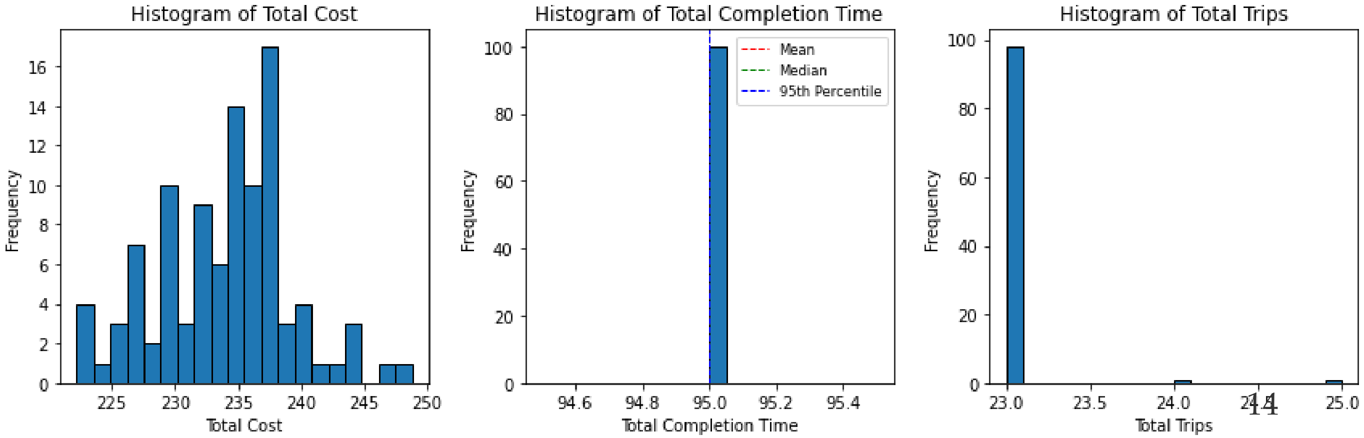


Case Study – Min Cost – Efficiency

Under 10% Worst Case Scenarios

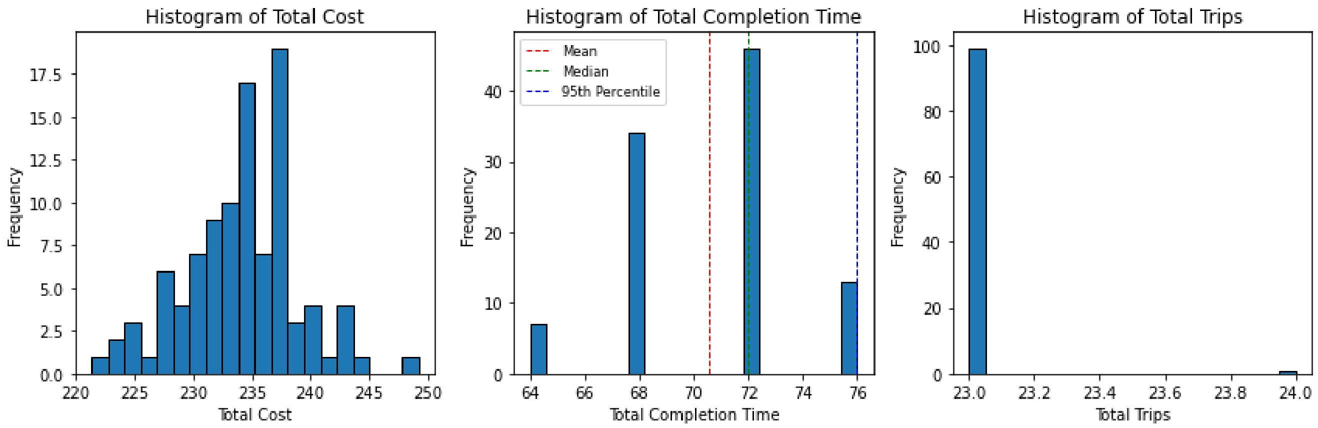


Under 10% Worst Case Scenarios & Max Acceptable 95th %-tile Worst-Case

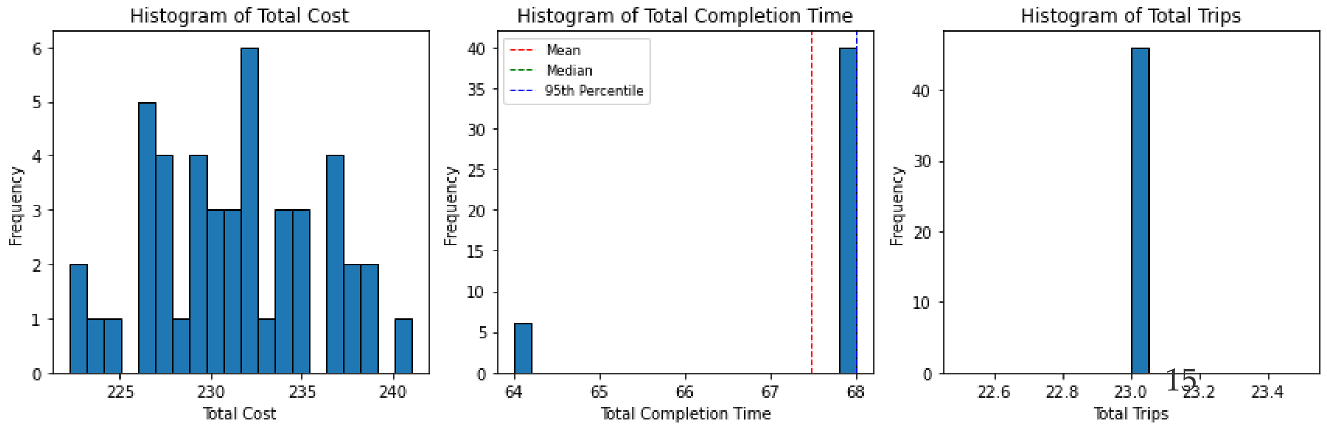


Case Study – Min (Multi Objective)

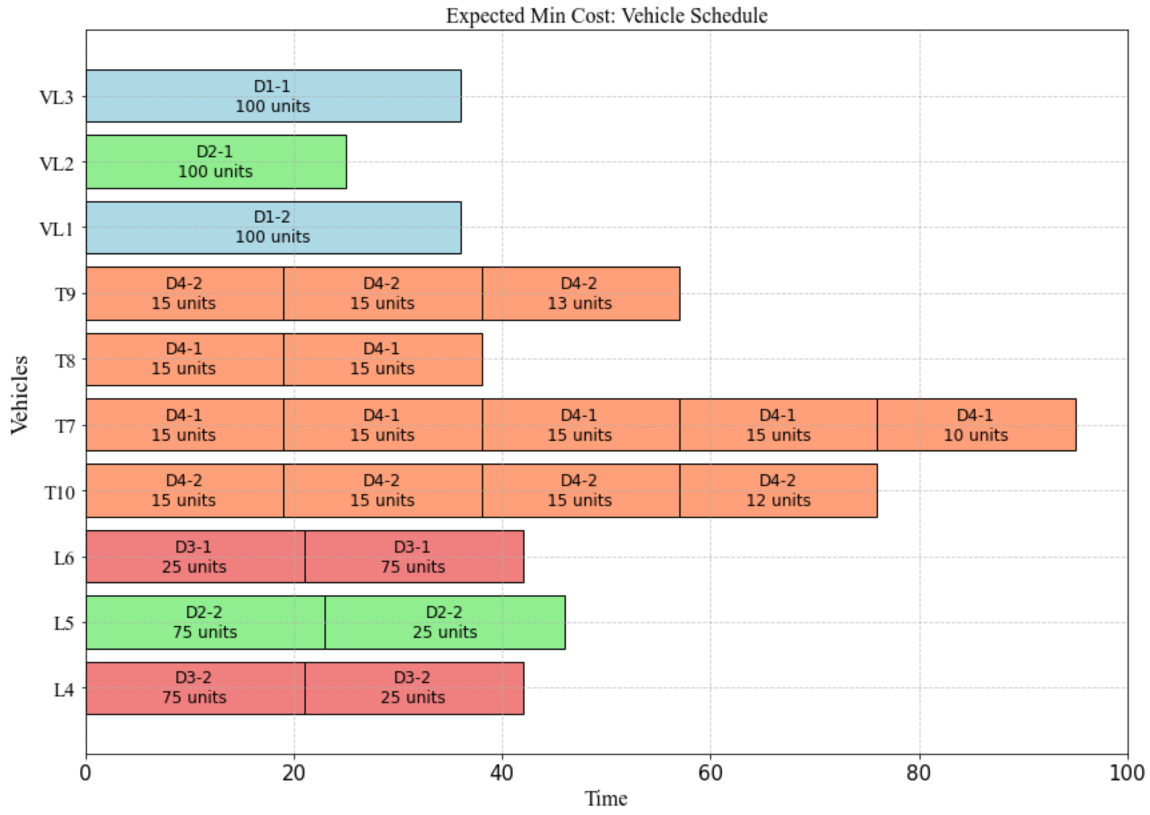
Under 10% Worst Case Scenarios



Under 10% Worst Case Scenarios & Max Acceptable 95th %-tile Worst-Case



Comparison of Objectives & Sample COA

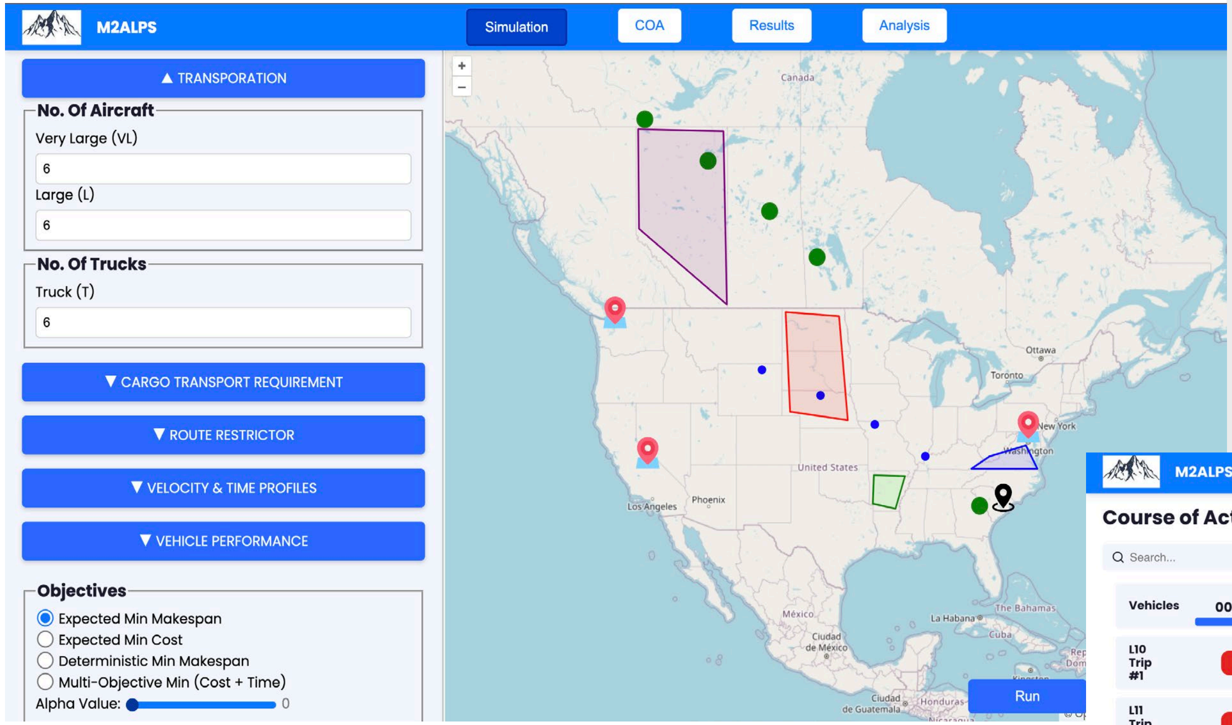


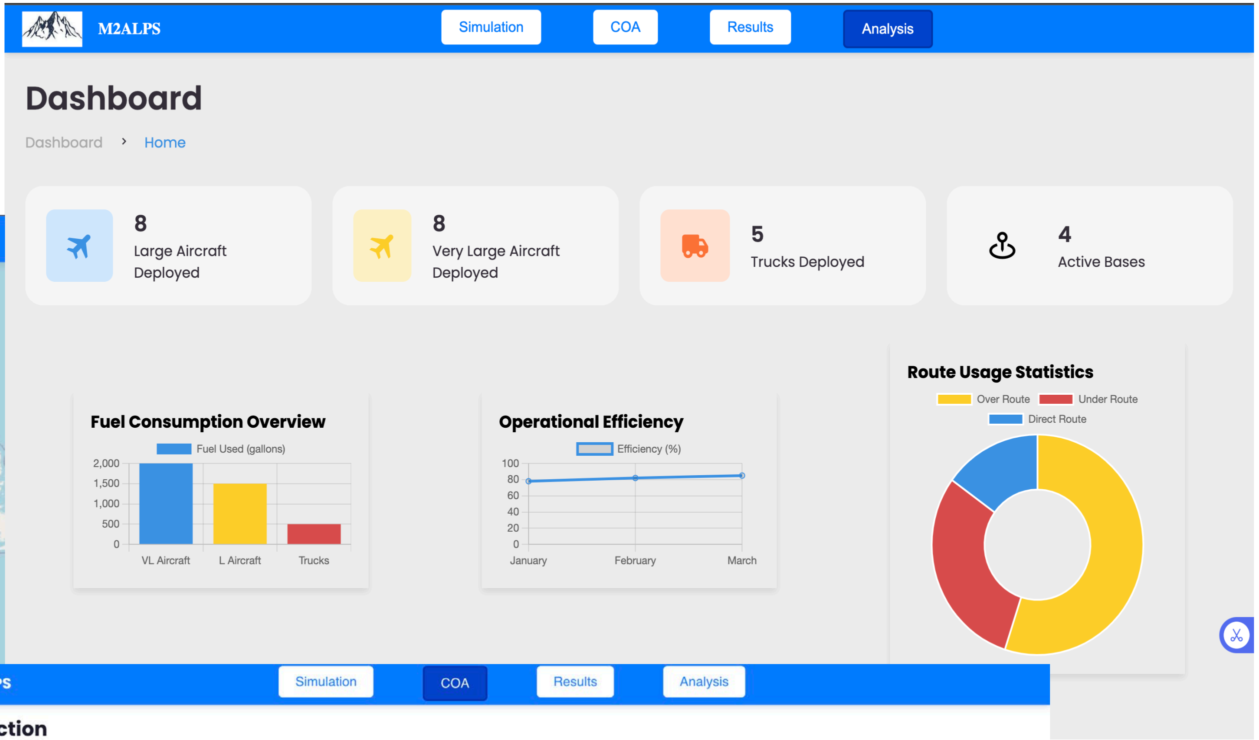
Total trips: 23
Total cost: 234.70
Total completion time: 95.00

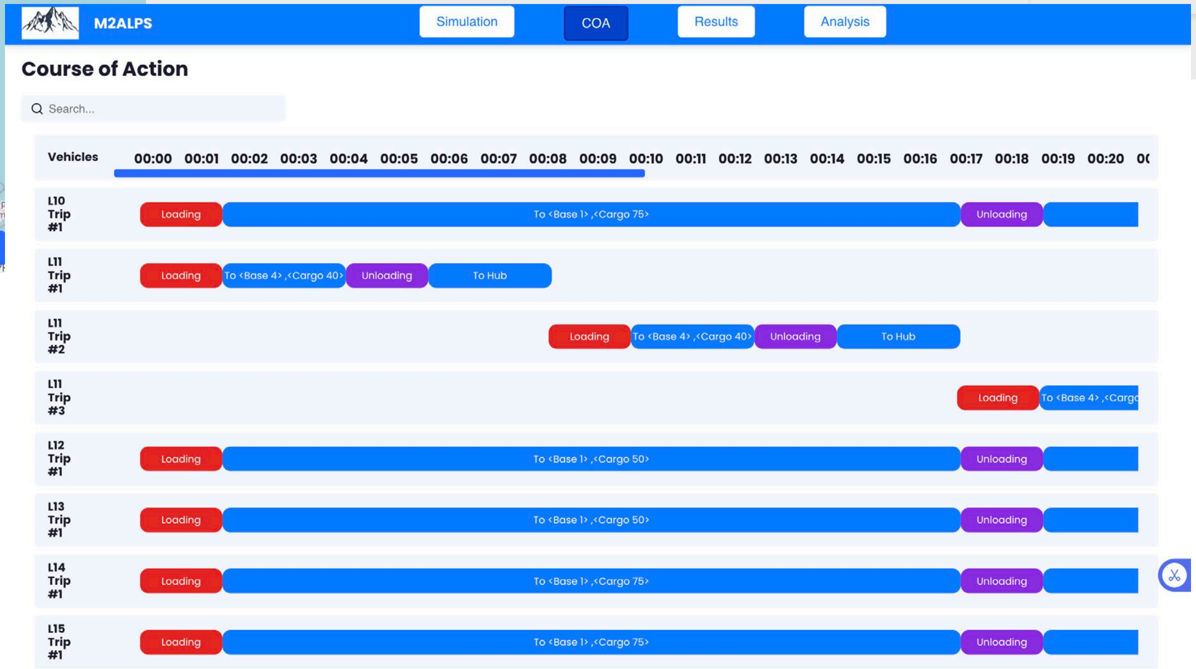
S: No	Objective	Total Time	Total Cost	Total Trips
1	Min Makespan	64	247	25
2	Min (0.5*Makespan + 0.5*Cost)	72	231	23
3	Min Cost	95	234	23

Table 2: Comparison Between Objective Values

M2ALPS – Tool Kit

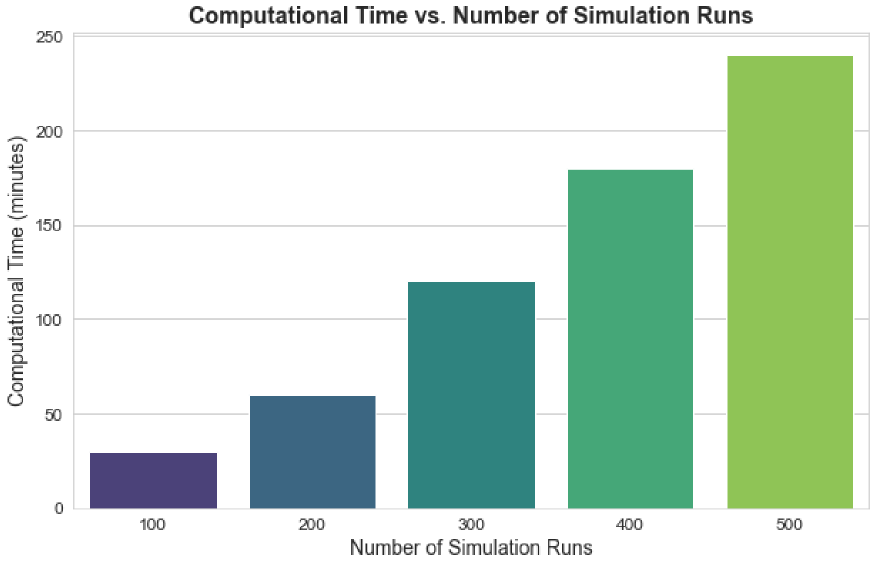






AI-Enabled Multi-Mode Adaptive Logistics Planning System (M2ALPS)

- Computational Time to run 100 scenarios using SMA takes ~ 30 to 40 Minutes
- Leveraging Machine Learning reduces computation time while maintaining accuracy in predicting key objectives.
- How can we use **AI-driven** methods to make better logistics decision-making – better solutions at computational quality?



Dataset – Simulation-Optimization

- **Input**
  - num_vl: Number of very large vehicles
  - num_l: Number of large vehicles
  - num_t: Number of trucks
  - vl_capacity: Capacity of very large vehicles
  - l_capacity: Capacity of large vehicles
  - t_capacity: Capacity of trucks
  - processing_V_D: Processing time for each vehicles at the corresponding demand locations
  - Demand_D: Demand Qty at each Demand location
- **Output**
  - total_trips: Total number of trips predicted
  - total_cost: Predicted cost for each trip
  - total_time: Predicted competition time for each trip
- Ran 2000 runs for the two objectives (Time, Cost)

Machine Learning – To Predict Objectives

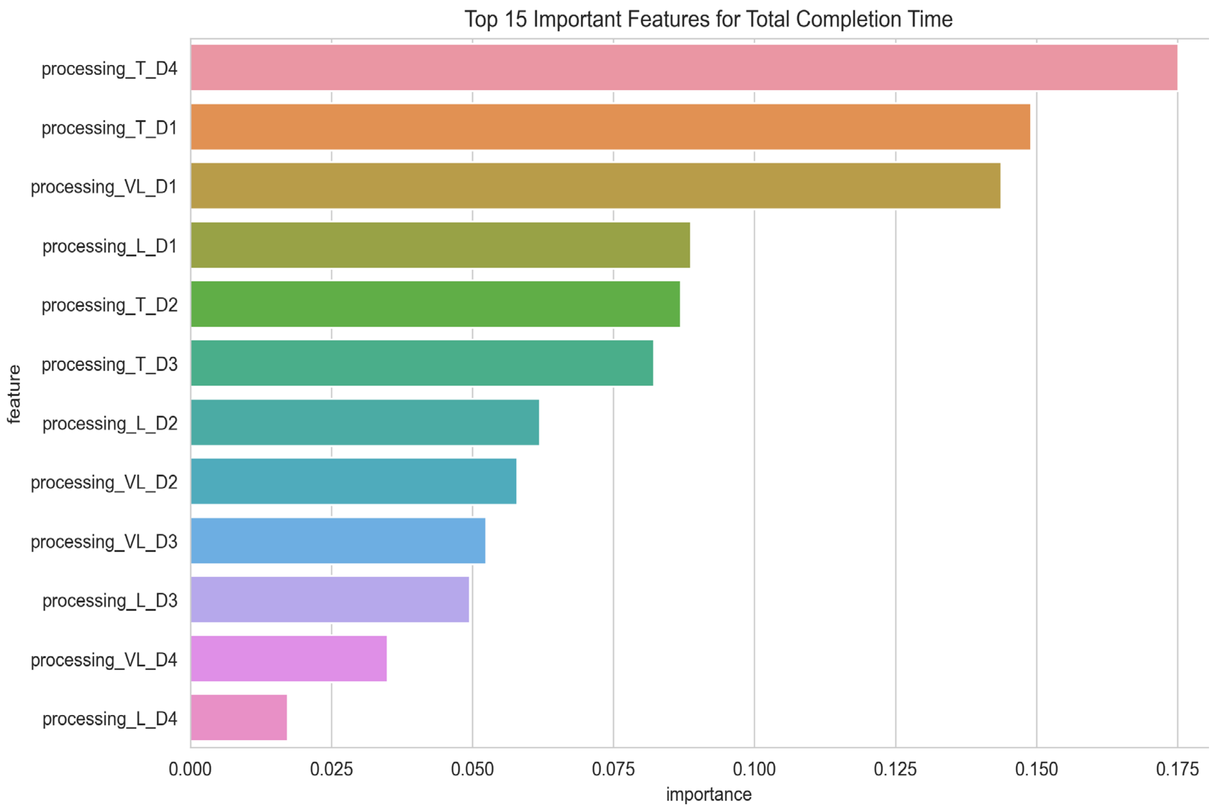
- Utilize data generated from simulation-optimization
- Random Forest to predict key logistics metrics: Total Completion Time and Total Cost
- Extracted feature importance to identify the most influential variables driving these outcomes
- Generated decision trees to reveal critical thresholds and decision points for logistics optimization

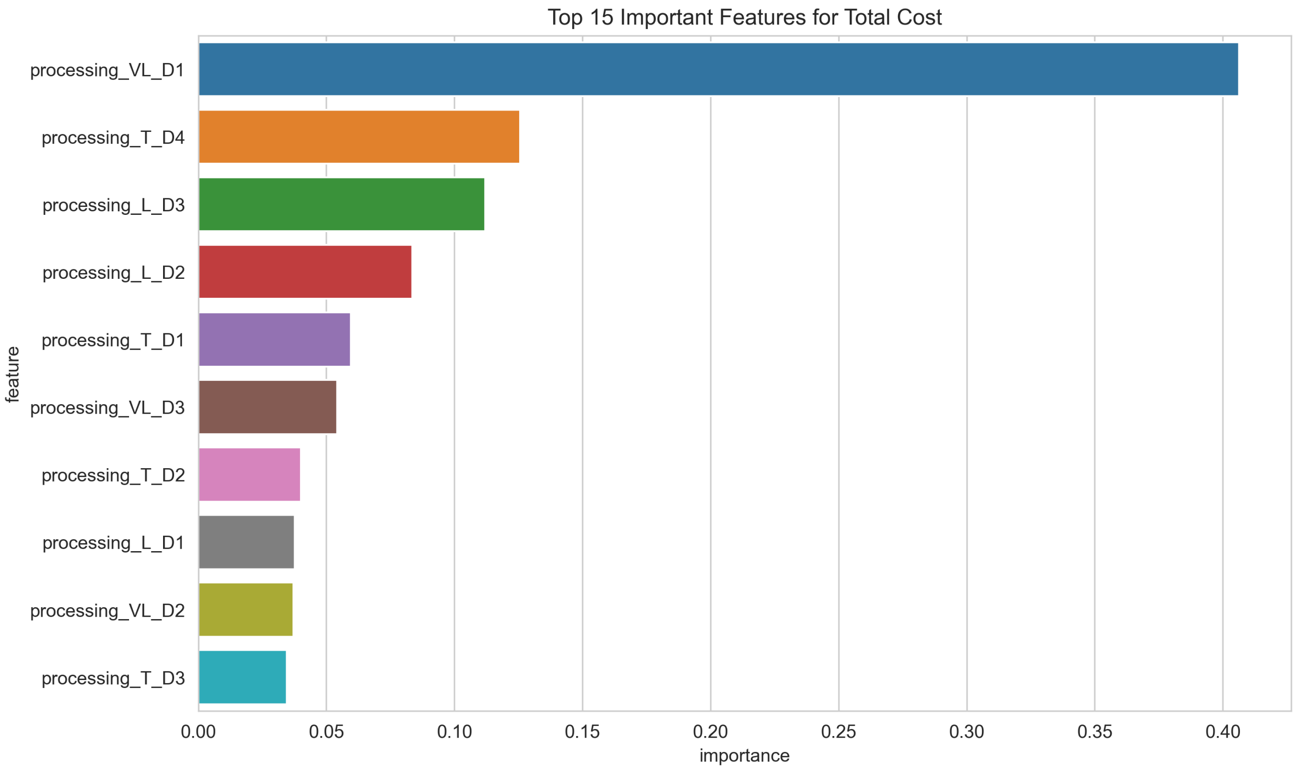
Training of Random Forest & Decision Trees

S : No	Model	Objective	RMSE	R2
1	Random Forest	Total Time	2.85	0.79
2	Decision Tree Regressor	Total Time	4.20	0.71
3	Random Forest	Total Cost	2.25	0.82
4	Decision Tree Regressor	Total Cost	3.50	0.75

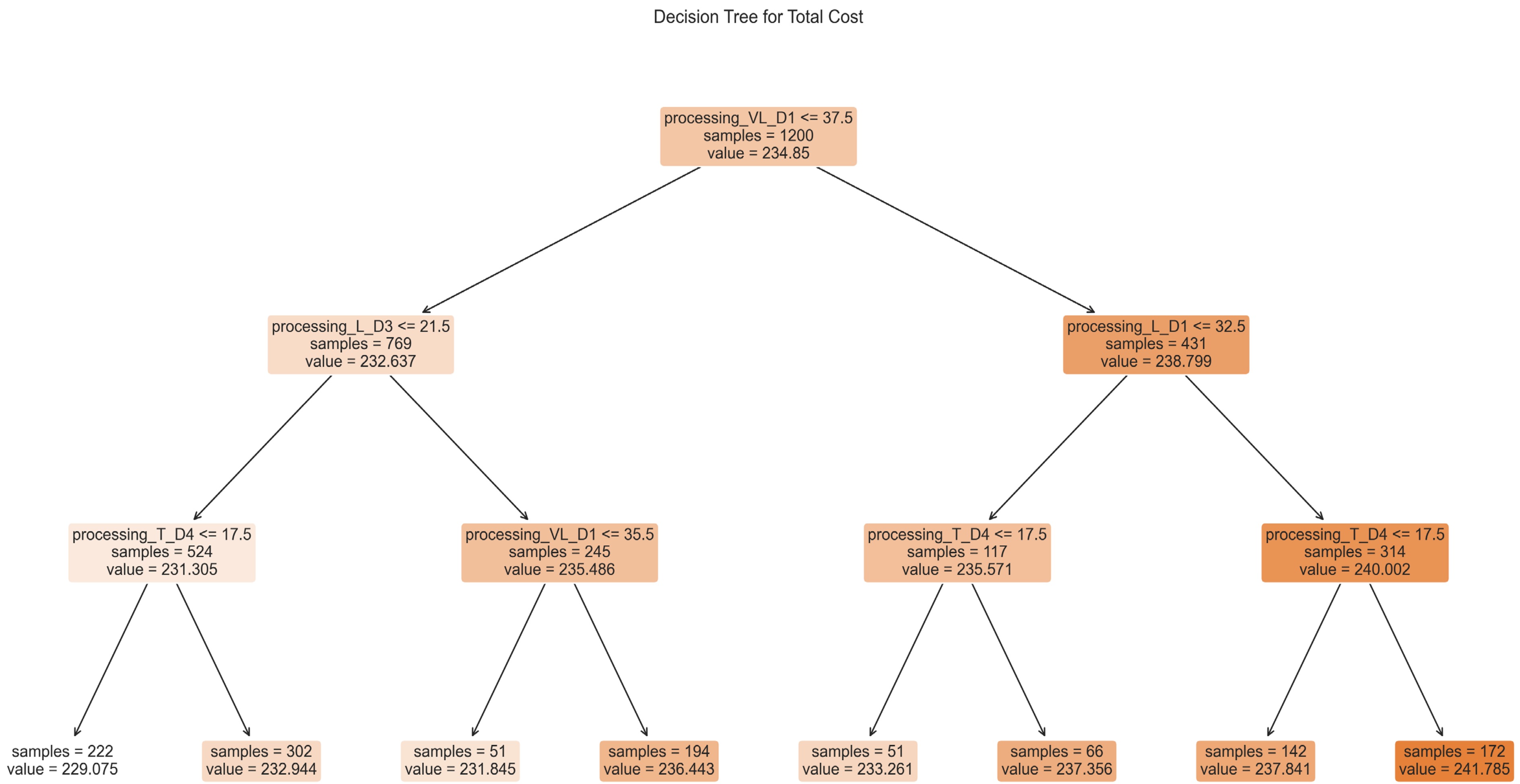
Table 3: Performance Metrics of the machine learning models

Feature Importance - Total Completion Time & Cost

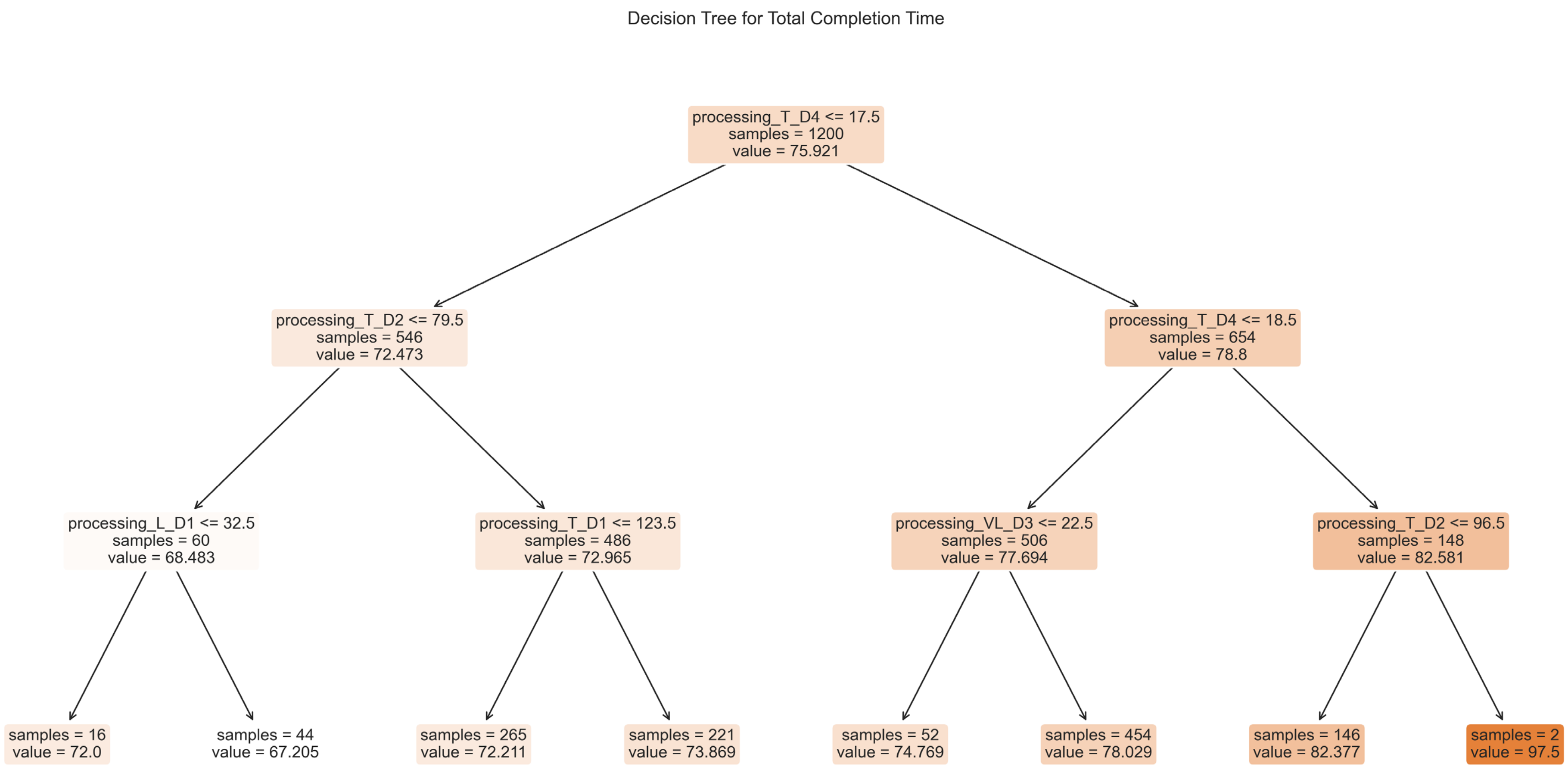




Decision Trees - Total Completion Time



Decision Trees - Total Cost



Inference on Total Completion Time

- The most critical factor for completion time is **truck processing at D4**, with a threshold of 17.5 units; keeping this below 17.5 significantly reduces completion time
- If **trucks** process quickly at D4 (≤17.5), **truck processing at D2** (threshold of 79.5 units) becomes the next key factor for further optimization
- For **slower trucks** at D4 (>17.5), further optimization is possible if **trucks can process at D4** in 18.5 units or less
- Efficient truck processing at both D4 and D2 highlights the **VL vehicles' processing at D3** (threshold 22.5) as the next important factor
- The tree shows a hierarchy: **Truck processing > VL processing > L processing** in impact on completion time

Inference on Total Cost

- **VL vehicle processing at D1** is the most critical factor for cost (threshold: 37.5 units), followed by **L vehicle processing at D3** (threshold: 21.5 units) in faster scenarios at D1
- For **slower VL vehicles** at D1 (>37.5), **L vehicle processing at D1** becomes important (threshold: 32.5 units)
- **Truck processing at D4** (threshold: 17.5 units) impacts total cost across multiple scenarios
- The cost-impact hierarchy is **VL processing > L processing > T processing**
- **Efficient processing of vehicles across D1-D4** is key for optimizing total cost

Conclusion

- Developed a multi-mode worst case stochastic optimization model
- Utilized sample median approximation method to simulate numerous scenarios and optimal decisions
- Running scenarios > 100 took higher computation time
- Applied machine learning techniques to obtain feature inference for the multi-mode logistic optimization problem
- Need for more nuanced ML models to predict decisions for vehicle allocations

Acknowledgement

This material is supported by the US Airforce Centre. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the AFCENT.

We would like to thank AFCENT for providing us with data and networks.

Thank You!

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