Machine Learning Final Project

The Future of AI and the Foundations of Machine Learning

A Risk-Aware Approach to Stochastic Resource Allocation

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1. The Future of AI

I envision a shift to autonomous, self-healing orchestration, transforming airports into **stochastic control systems**. Unlike current deterministic planning, future AI will anticipate disruptions and optimize for resilience rather than just throughput. As the airport's central nervous system, it will enable real-time negotiation with airlines, maintain dynamic safety buffers based on volatility, and mathematically guarantee fairness to prevent winner-takes-all scenarios.

2. Ingredients Needed

To realize the capability described in Question 1, the following ingredients are essential:

- Data (omniscient perception): Requires petabyte-scale, real-time multimodal streams—ranging from structured schedules to unstructured cockpit audio and environmental sensors. This serves as the AI's sensory input to perceive the physical reality beyond simple databases.
- Tools (reasoning & control):
  - Graph neural networks: To model the airport's spatial topology (gates/taxiways) and physical constraints (maintenance/accidents).
  - World models: To simulate millions of "what-if" scenarios and predict future states before taking action.
  - Hierarchical reinforcement learning: To coordinate high-level strategic planning with low-level tactical execution.
- Environment (digital twin): A high-fidelity, 1:1 synchronized simulation acting as a "safety sandbox," where critical decisions are verified before physical implementation.
- Learning Setup:
  - Self-supervised pre-training: To learn operational dynamics from decades of unlabeled historical data.
  - Reinforcement learning from human feedback: To integrate human feedback for resolving ethical dilemmas with safety values.

3. Machine Learning Paradigms Involved

Realizing this requires a neuro-symbolic hybrid system, primarily driven by reinforcement learning (RL) supported by self-supervised learning (SSL).

- Primary: Reinforcement learning
  - Reason: Airport operations involve sequential decision-making under uncertainty. Unlike supervised learning which mimics historical data, RL explores novel strategies to maximize long-term resilience.
  - Mechanism: It operates in a *real-time closed loop*. The agent observes the comprehensive state from the digital twin and performs online learning to maximize a multi-objective reward function (balancing punctuality, fairness, and safety).
- Support: Self-supervised learning
  - Role: To construct internal *world models*. By pre-training on vast unlabeled data to predict future states, the AI learns the causal dynamics of the environment. This enables sample-efficient planning (simulation) without relying solely on real-world trial-and-error.

4. The First Step: A Solvable Simplified Model

To bridge the gap between current heuristics and the future vision, I propose a risk-aware stochastic bin packing model as a feasible first step.

4.1. Problem Formulation

We model airport gate assignment as a one-dimensional bin packing problem. Gates are bins with capacity $C = 1$, and flights are items. However, deterministic algorithms like best-fit decreasing (BFD) pack flights tightly to minimize gate usage; in a stochastic environment where flight durations fluctuate, this leaves zero margin for error. A slight delay causes an overflow (gate conflict).

Now, instead of a fixed buffer, we train an AI agent to determine the optimal safety margin for each flight.

- Input: The agent observes the flight's nominal duration s_i and a volatility score σ_i.
- Action: The agent outputs a specific safety padding β_i.
- Execution: We pack the flights using BFD based on their effective size $\hat{s}_i = s_i + \beta_i$.

We simulate the actual stochastic duration with $\ln S_i \sim \mathcal{N}(\ln s_i, {\sigma_i}^2)$. The goal is to minimize

$$\mathbb{E}\left(\#\mathrm{bins}(\hat{s}) + \lambda \cdot \sum_j \max\left(0, \sum_{i \in \mathrm{bin}_j} S_i - C\right)\right), \tag{4.1.1}$$

which forces the model to learn a non-trivial trade-off: padding high-variance flights to ensure robustness while packing low-variance flights tightly for efficiency.

This model is the perfect simplification because it requires no external real-world data (synthetic (s_i, σ_i) tuples are sufficient) yet captures the core logic of the 20-year vision: risk management under uncertainty.

4.2. Experimental Results

To validate the proposed model, we conducted experiments on a synthetic test set of $N = 5000$ flights. We employed a multi-seed evaluation framework (using seeds 11, 16, 52, 0, and 4) to ensure the stability and reproducibility of the reinforcement learning agents. The AI models were trained under three different penalty weights ($\lambda \in \{75, 100, 125\}$) and compared against deterministic baselines: a "naive" strategy (0% padding) and "fixed buffer" strategies (adding 4.5%, 5%, and 5.5% padding to all flights).

4.2.1. Simulation Parameters and Real-World Mapping

To ensure the simulation reflects realistic airport operations, we calibrated the parameters based on typical flight turnaround times:

- Nominal duration ($s \in [0.1, 0.25]$): Assuming a gate operates for approximately 20 hours per day ($C = 1.0$), the range corresponds to turnaround times of 2 to 5 hours. This effectively captures the mix of traffic at an international hub, ranging from standard regional flights ($s = 0.1$) to complex wide-body long-haul operations ($s = 0.25$).
- Volatility ($\sigma \in [0.01, 0.2]$): The volatility parameter models the uncertainty in duration. A low σ represents routine, predictable operations, while a high σ (up to 0.2) models high-variance scenarios where a 5-hour turnaround could fluctuate due to weather or maintenance issues. We explicitly correlated σ with s in our data generation to reflect that longer flights naturally accumulate more variance.

4.2.2. Efficiency vs. Robustness Trade-off

The experimental data reveals a distinct trade-off between resource efficiency (minimizing gates) and operational robustness (minimizing overflow).

As shown in Figure 1 and Figure 2, the "naive" strategy yielded unacceptable total overflow (> 17 units), confirming that safety buffers are mandatory in stochastic environments. See Table 1 for the key findings from the valid strategies and see Figure 3 and Figure 4 for comparisons between non-naive models.

4.2.3. Key Insight: The Efficiency Sweet Spot

The most significant result is the performance of the $\lambda = 75$ agent. Unlike fixed strategies that apply a blanket buffer to every flight, the RL agent learned to dynamically allocate padding based on volatility (σ_i).

- Resource savings: The AI ($\lambda = 75$) used an average of 1,105 gates for a week, saving approximately 47 gates for a week compared to the most competitive baseline (cf. the fixed-4.5% model used 1,152 gates).
- Marginal risk: While this aggressive strategy increased the total overflow to 0.65 (cf. 0.15 for Fixed 4.5%), this represents a negligible delay when distributed across 5,000 flights ($\approx 1.3 \times 10^{-4}$ units per flight).

This demonstrates that the AI identified non-trivial optimization opportunities that rigid heuristics missed.

4.2.4. Controllability of Risk Appetite

The experiments validated the theoretical responsiveness of the loss function (4.1.1) to the penalty weight λ:

- Aggressive mode ($\lambda = 75$): The agent prioritizes gate reduction, suitable for cost-saving operations during off-peak hours.
- Safety-first mode ($\lambda = 125$): The agent adopts a "zero-tolerance" policy for overflow. As seen in Figure 3 and Figure 4, its gate usage rises to match the Fixed 5% strategy, but it achieves near-perfect robustness.

In conclusion, the proposed risk-aware stochastic bin packing model not only outperforms static baselines in efficiency but also provides a tunable mechanism to align operational decisions with the airport's changing risk tolerance.

4.2.5. Real-World Interpretation: From Simulation to Infrastructure

To ensure our findings are grounded in reality, we map the simulation parameters to actual airport operations:

- Assumption (Gate-Days): A major international hub handles approximately 700–800 flights per day; cf. TPE hendled 728 flights per day in 2019. Therefore, our test set of $N = 5,000$ flights represents roughly one week of airport traffic. In this context, the "bins" in our model correspond to "Gate-Days" (one gate available for one day).
- Infrastructure Impact: The experimental results show that the AI agent ($\lambda = 75$) reduces the total requirement by **47 bins** compared to the fixed-4.5% baseline.

$$\begin{aligned}\text{Daily Savings} &= 47 \cdot \frac{\text{Gate-Days}}{7} \text{ Days} \\ &\approx 6.7 \text{ Physical Gates}\end{aligned}$$

- Conclusion: This translates to saving at least **6 physical gates per day**. In terms of infrastructure, this is equivalent to avoiding the construction cost of a small satellite terminal while maintaining the same operational throughput. This proves that the AI's value is not just theoretical but carries significant financial implications.

4.3. Discussion

The simplified model serves as a critical proof-of-concept for the 20-year vision. By solving this proxy problem, we gained valuable insights that directly inform the roadmap toward a fully autonomous airport orchestration system.

4.3.1. What We Learned from the Simplified Model

1. Dynamic Buffering Works: The experiment proved that a "one-size-fits-all" buffer (e.g., Fixed 4.5%) is inefficient. An AI agent can learn to discriminate between high-variance and low-variance flights, allocating resources only where necessary. This confirms that uncertainty is manageable if modeled correctly.
2. The Cost of Absolute Safety: The results from the $\lambda = 125$ agent revealed that achieving zero overflow comes at a disproportionately high cost in resource usage. This teaches us that "optimal" operations are not about eliminating risk entirely, but about finding the efficient frontier of risk vs. cost.

4.3.2. Implications for the Grand Challenge

This solvable model highlights two key challenges for the future full-scale system:

1. Data Dependency: The success of our agent relied on accurate volatility scores (σ_i). In the real world, estimating this uncertainty from multimodal data (weather, mechanics, crew stress) will be the single most critical factor. If the uncertainty estimation is wrong, the dynamic buffer fails.
2. Scalability of Reinforcement Learning: While REINFORCE worked well for this 1D problem, the variance in training (as seen across different seeds) suggests that scaling to a full airport graph with thousands of constraints will require more stable algorithms (like PPO or distributional RL) and a robust simulation environment (Digital Twin) to ensure reliable convergence.

5. Acknowledgement

I would like to express my gratitude to Prof. Te-Sheng Lin for his time consulting with me about my idea regarding this project. Also, I want to thank Wei-Hsiang Lo about his idea; his idea really expedited my work.

6. Appendix

Table 1. Performance statistics summary ($N = 5000$ flights).

Strategy	Type	Average Gates Used (*Efficiency*)	Average Overflow (*Robustness*)
Fixed (4.5%)	Baseline	1,152.0	0.15
Fixed (5%)		1,185.2	0.06
Fixed (5.5%)		1,218.5	0.04
AI ($\lambda = 75$)	RL Agent	**1,104.9**	0.65
AI ($\lambda = 100$)		1,152.7	0.21
AI ($\lambda = 125$)		1,159.8	**0.17**

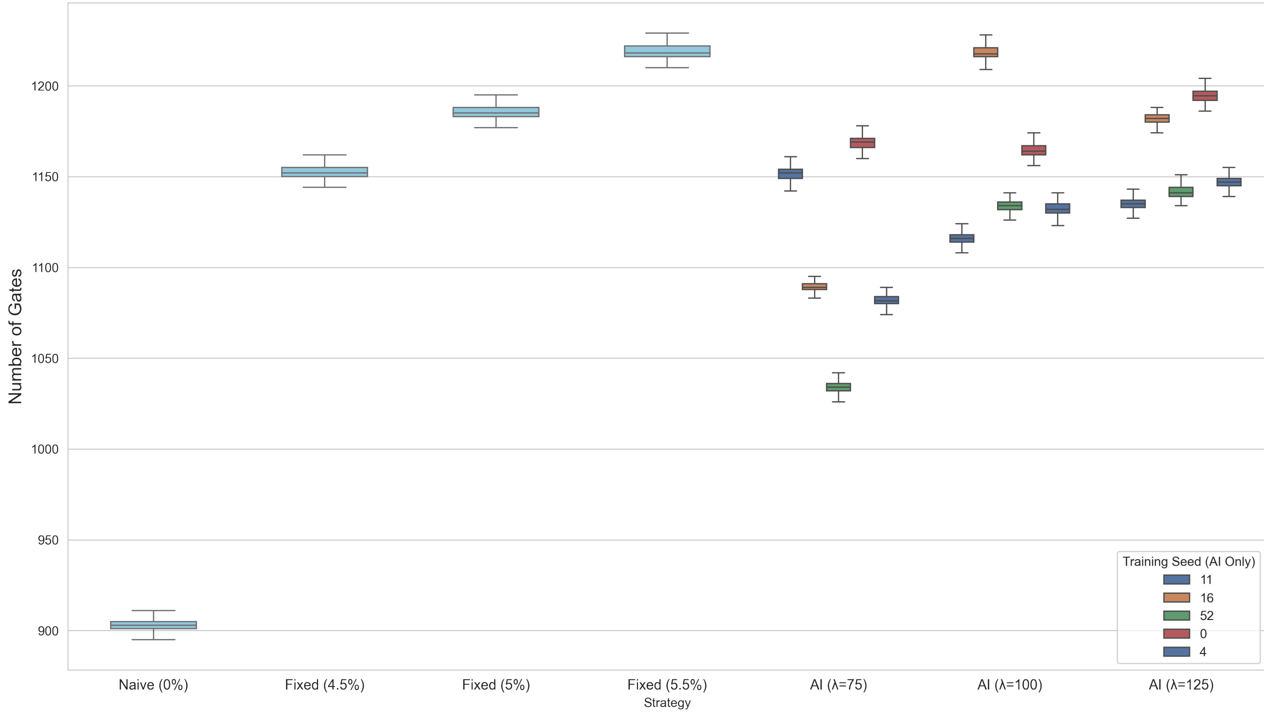

Figure 1. Efficiency comparison for all models.

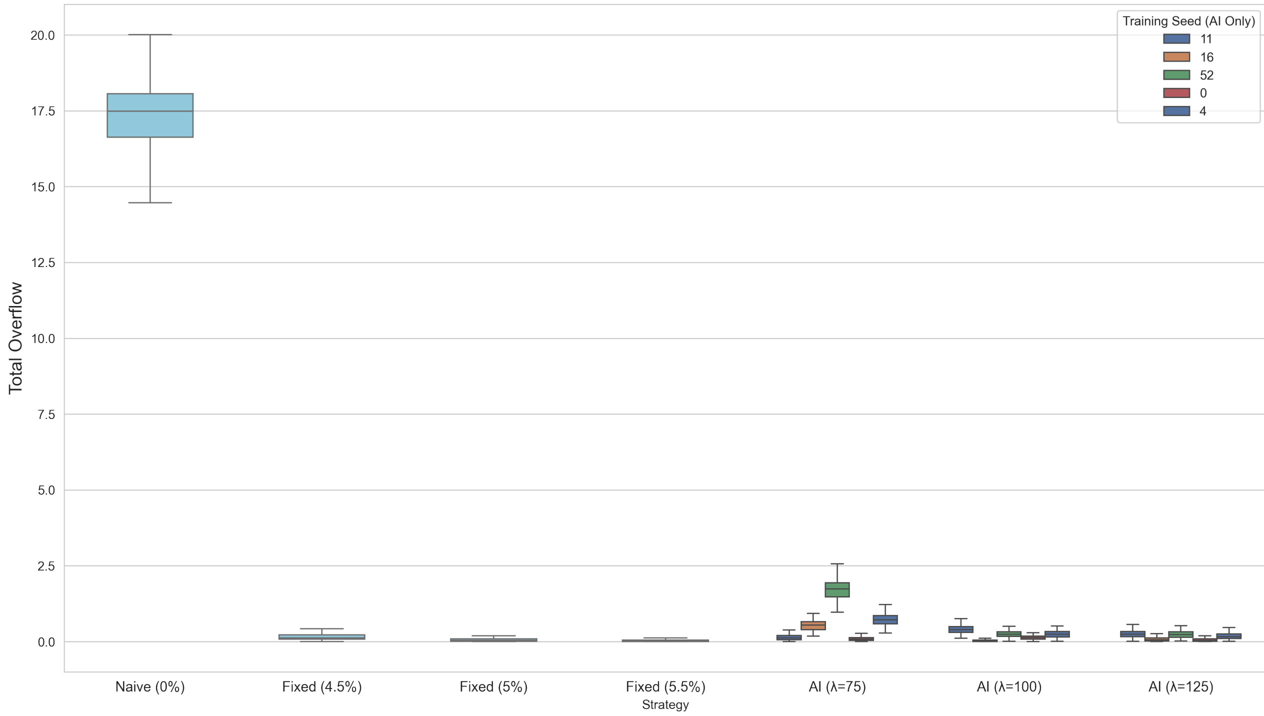

Figure 2. Robustness comparison for all models.

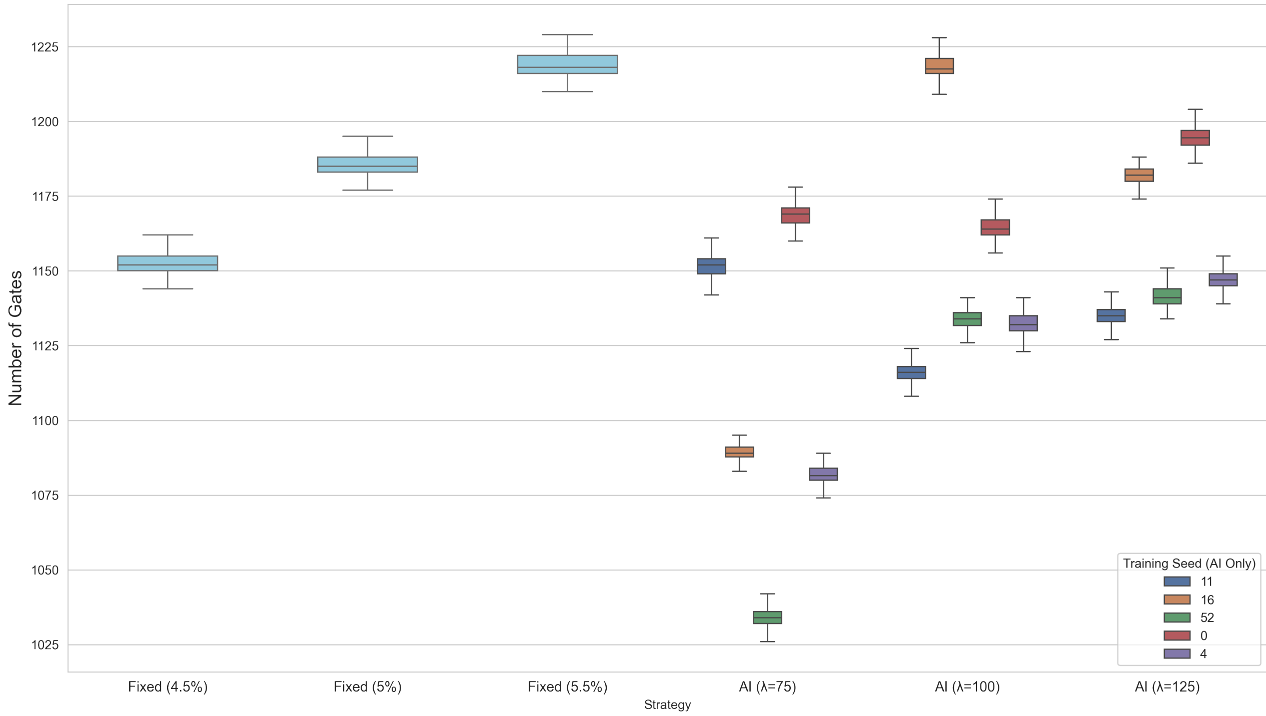

Figure 3. Efficiency comparison: The AI agent ($\lambda = 75$) reduces gate usage compared to baseline models.

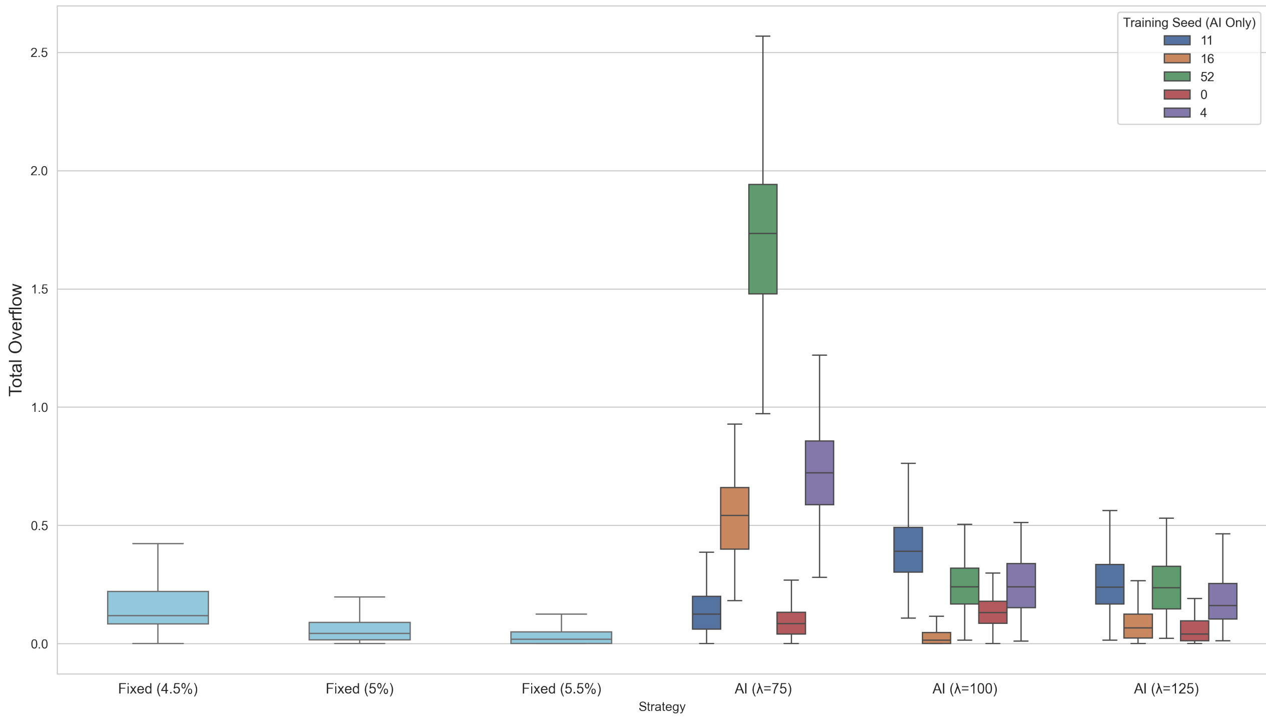

Figure 4. Robustness comparison: While the aggressive AI ($\lambda = 75$) incurs marginal overflow, the conservative AI ($\lambda = 125$) matches the zero-overflow performance of baseline models.