Active Learning for Air Traffic Management Simulation Metamodeling

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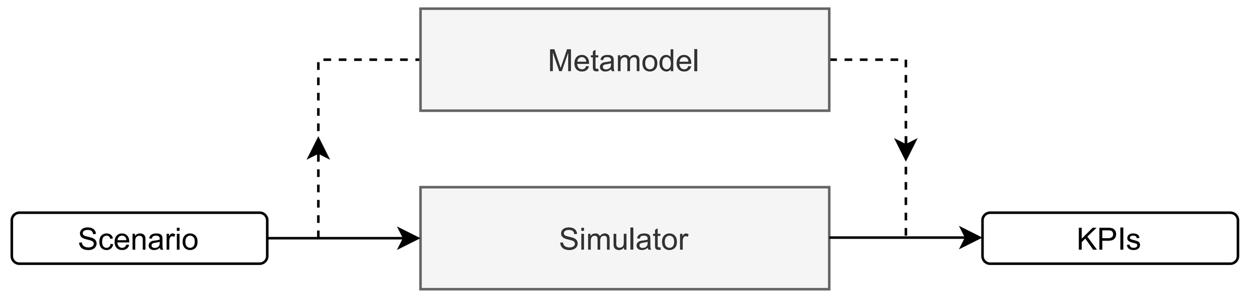
Motivation

Simulators are often the go-to tools to explore future scenarios or new policies, but complex, stochastic simulators tend to be slow. So how do we efficiently explore the simulator?



Idea: Bypass the expensive simulator with another model

Approach

Integrate simulation metamodeling and active learning.

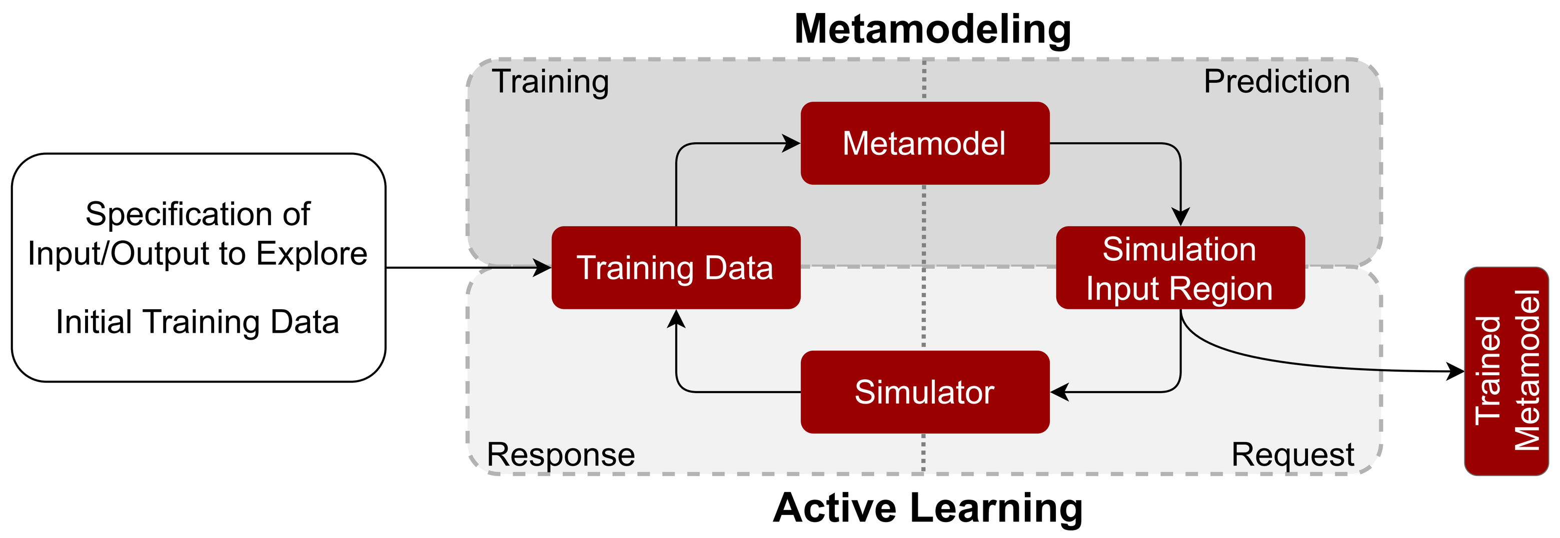


Figure 1: Main steps of the proposed active learning metamodeling methodology.

Metamodeling

Approximate the simulator by another model - a metamodel

1. Generalize well from small data sets
2. Uncertainty quantification
3. Predicting super fast!

Active Learning

Choose what to simulate to get the most accurate metamodel

1. Efficient exploration of the simulation input space
2. Avoiding redundant simulations
3. Self-guided

Case Study

Simulator: Mercury

Stochastic event-driven micro-level agent-based model designed to mimic the movements of both flights and passengers.

Policy Analysis

How the passenger compensation threshold and magnitude affect delays and cost per flight.

var	name	description	values
x_1	compensation_magnitude_long1	Compensation between first and second thresholds for long-haul passengers in euros (€).	[0, 500, 1000,. . . , 5000]
x_2	first_compensation_threshold.	Threshold of arrival time after which the passengers receive a compensation in minutes.	[0, 60, 120,. . . , 480]
x_3	fuel_price	Price per kilogram of fuel in euros (€).	[0, 0.5, 1,. . . , 5]
y_1	arrival_delay_min_mean	Average arrival delay per flight in minutes.	real-valued
y_2	departure_delay_min_mean	Average departure delay per flight in minutes.	real-valued
y_3	total_cost_mean	Average total cost per flight operation in euros (€)	real-valued, positive
y_4	pax_tot_arrival_delay_mean	Average total arrival delay per passenger in minutes.	real-valued, positive
y_5	lcc_arrival_delay_min_mean	Average arrival delay per flight for low cost carriers in minutes.	real-valued
y_6	lcc_total_cost_mean	Average total cost per flight for low cost carriers in euros (€).	real-value, positive

Results: Active Learning

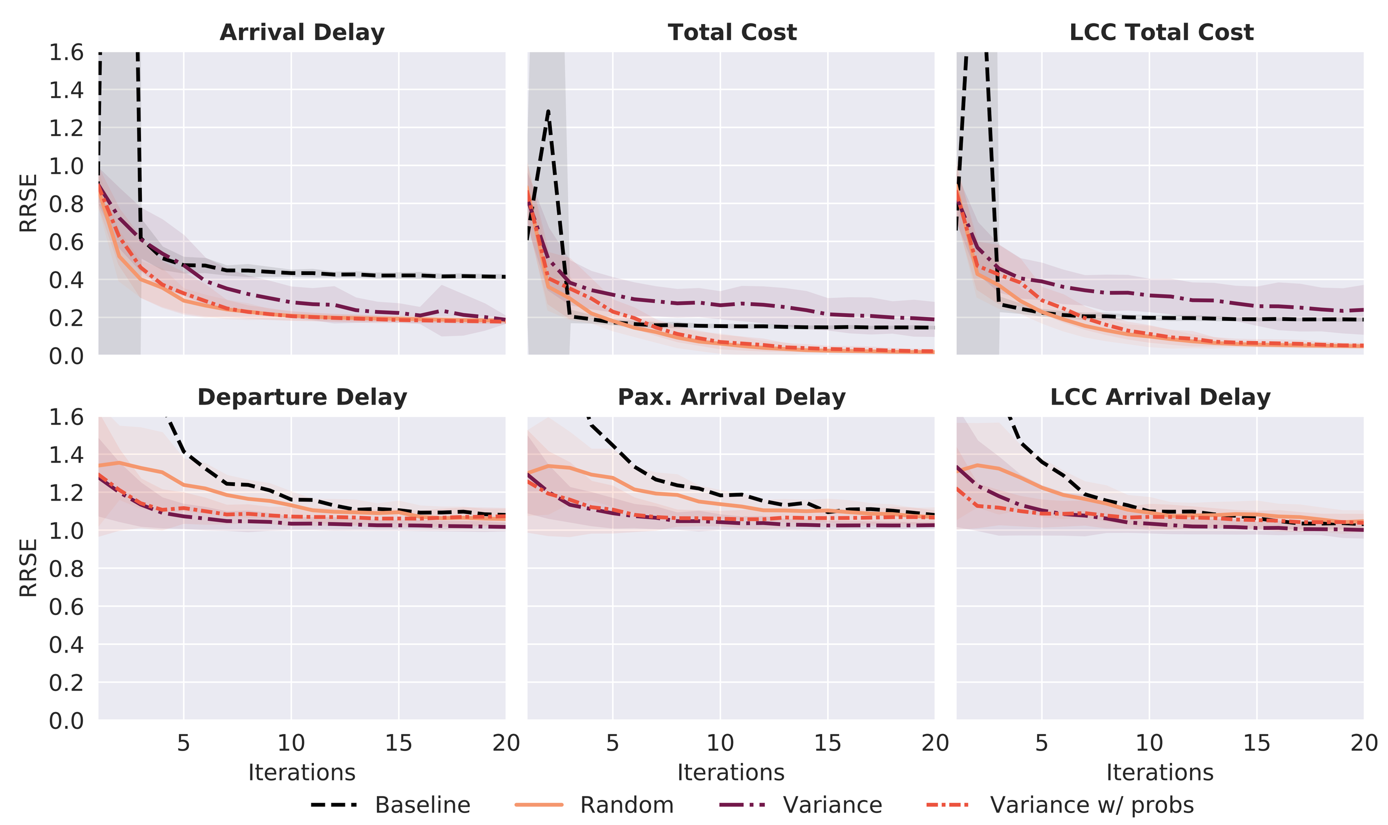


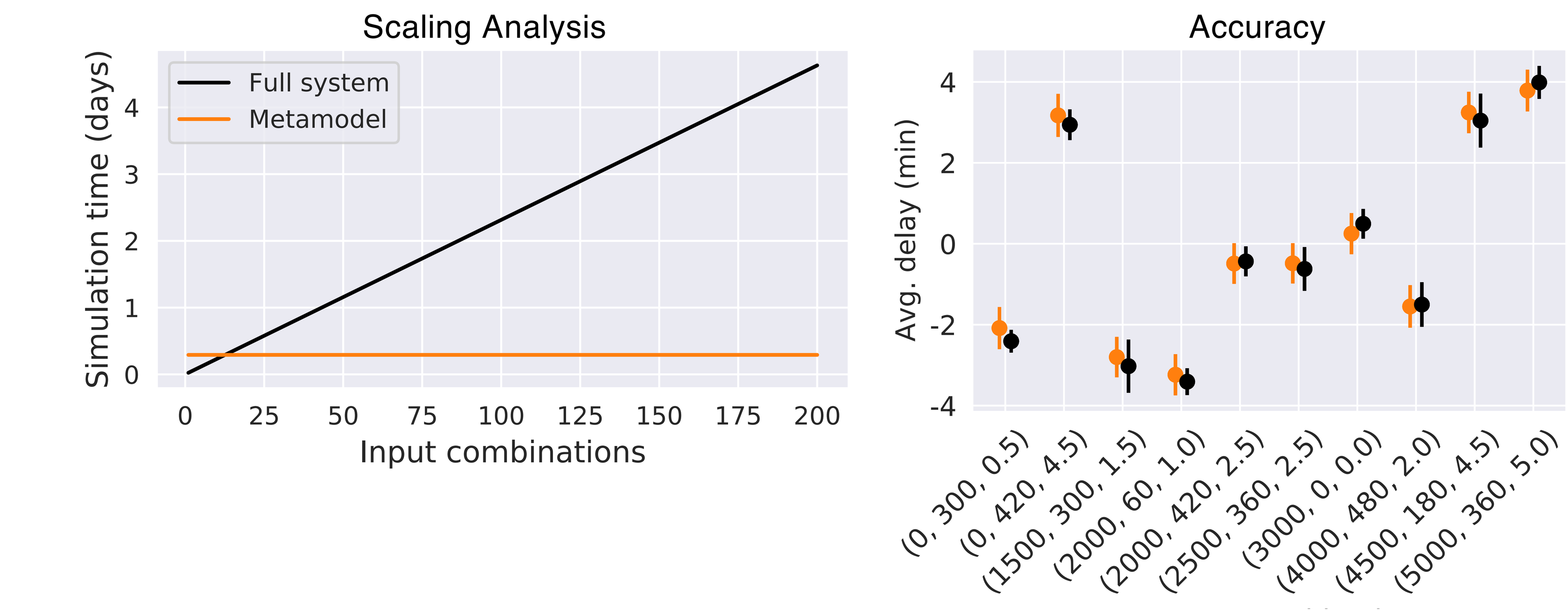
Figure 2: Performance of the baseline and three active learning strategies, averaged over 30 runs. The shaded regions show the ±1 standard deviations.

Results: Speed

Full system

We benchmark the framework against the traditional full system, where we explore the simulator by running it multiple times for specific scenarios (input combinations).

$$\text{Simulation time} = 10x \cdot 20\text{min}/6$$



Conclusions

Using the state-of-the-art ATM simulator, *Mercury*, and employing a Gaussian Process as a metamodel, we showed that active learning are capable of increasing the modeling performances of simulation metamodeling approaches in a more efficient way, alongside showing that the metamodel is an accurate and scalable solution.

What does this mean from a policy perspective?

We can do. . .

- A more comprehensive policy analysis in the same time
- The 'original' policy analysis in a shorter time
- Policy analyses that otherwise would be infeasible to do in practice due to long simulation times

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MLSM Machine Learning for Smart Mobility

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