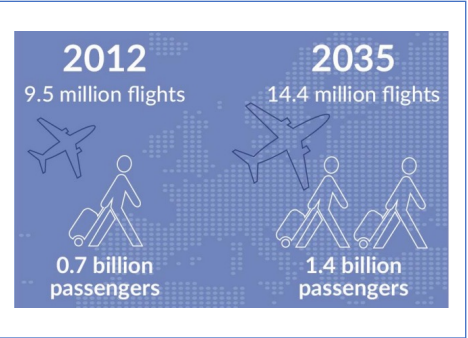
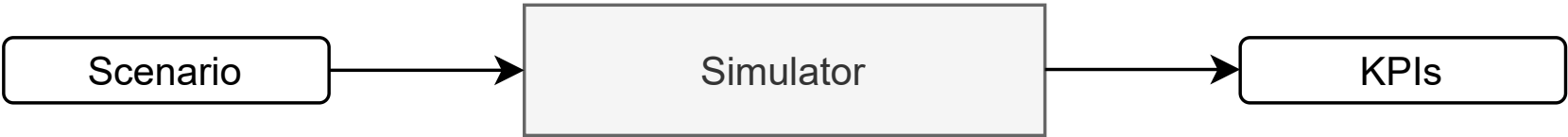


# Active Learning Metamodels for ATM Simulation Modelling

Christoffer Riis, Francisco Antunes, Gérald Gurtner, Francisco Camara  
Pereira, Luis Delgado & Carlos Azevedo



Simulators are often the go-to tools to explore future scenarios or new policies.

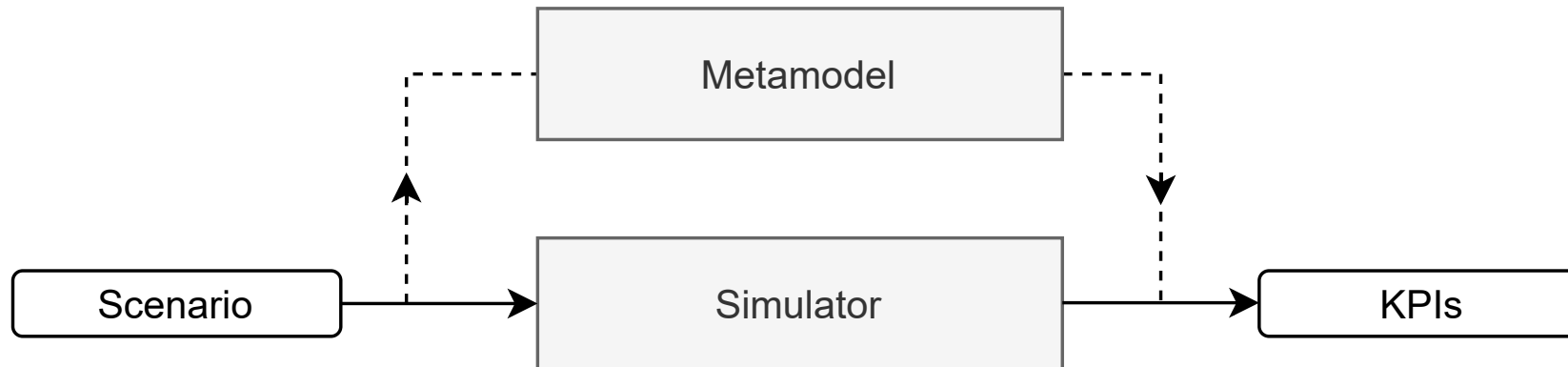


Complex and stochastic ---> tend to be slow

NOSTROMO is funded by the SESAR Joint Undertaking through the European Union’s Horizon 2020 research and innovation programme under grant agreement No 892517.

# Metamodeling

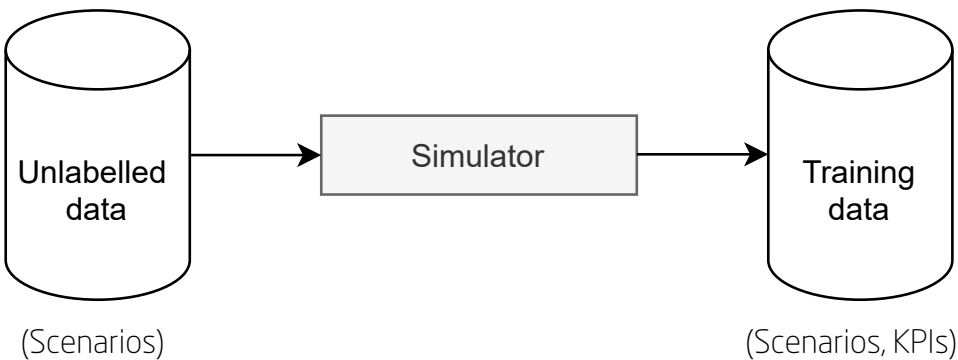
Can we bypass the expensive simulator with another model?



# Active Learning

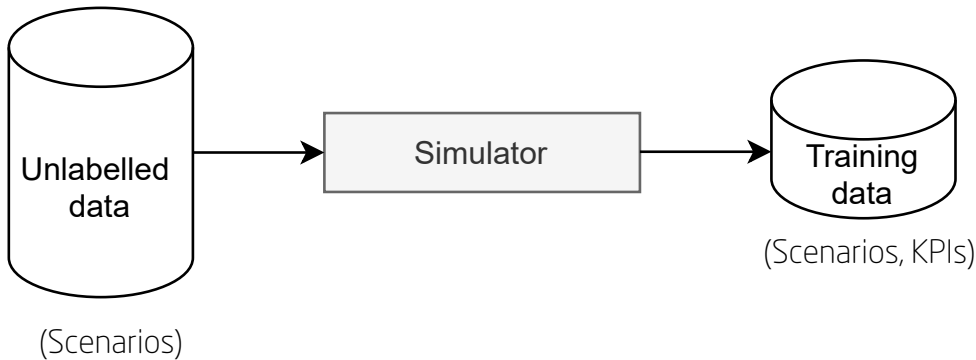
Fit a metamodel

The more simulations, the better



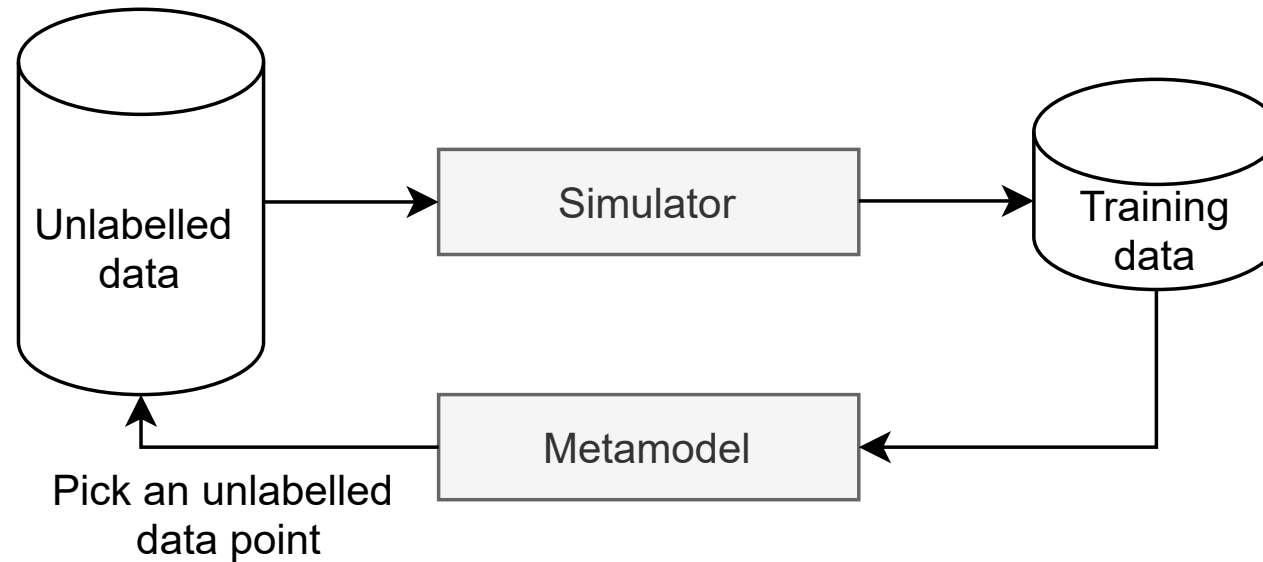
Keep simulation time low

The fewer simulations, the better



# Active Learning

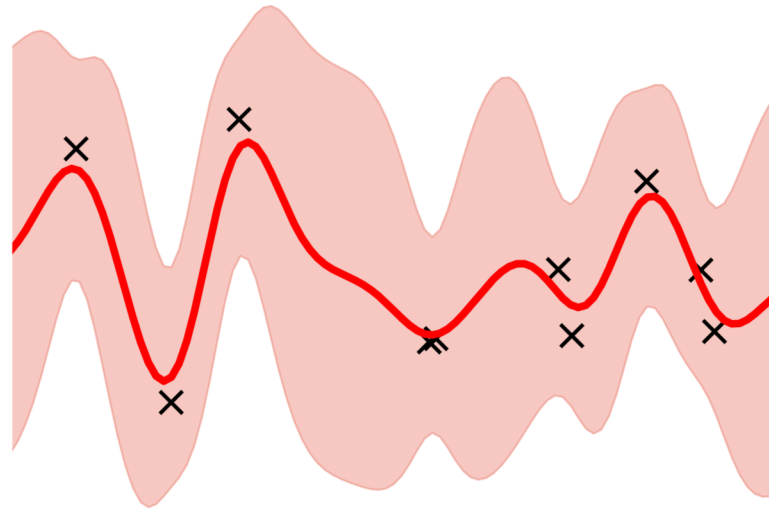
Iteratively pick a scenario to simulate to augment the training data



# Metamodel

## Gaussian Processes

- Generalize well from small data sets
- Uncertainty quantification



# Active Learning Strategies

Random      Pick a random data point

Variance      Pick the data point with most predictive variance

Variance  
with probs      Compute average variance for each output

$$\mu_i^{VAR} = \text{mean}(\text{var}(\text{output}_i))$$

Make probabilities:

$$p_i = \frac{\mu_i^{VAR}}{\sum \mu_i^{VAR}}$$

Draw a output with probability  $p_i$ , and find the point with most predictive variance

# Case study

## Mercury<sup>[1]</sup>

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         |

[1] L. Delgado, G. Gurtner, S. Zaoli, P. Mazzarisi, D. Valput, A. Cook, and F. Lillo, "Final tool and model description, and case studies results," Domino Project, Deliverable 5.3, 2019

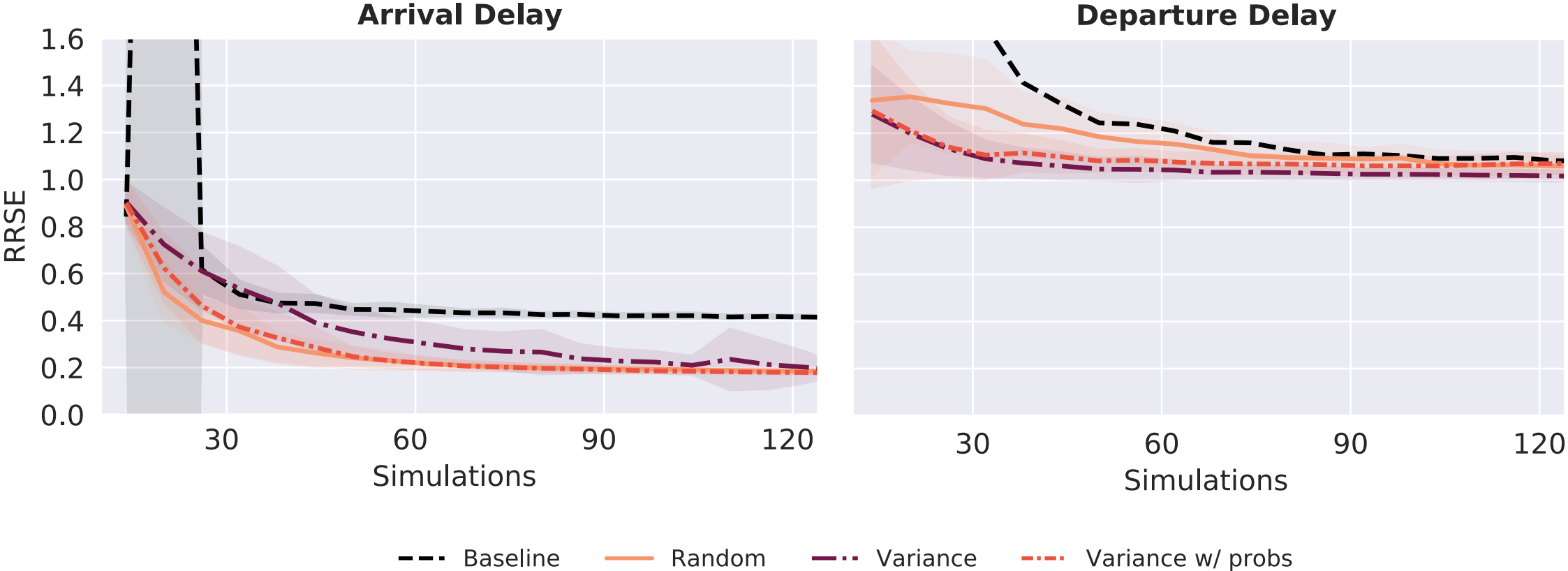
# Evaluation

RRSE: Root Relative Square Error

$$\sqrt{\frac{\sum_{i=1}^N (y_i - \hat{y}_i)^2}{\sum_{i=1}^N (y_i - \bar{y})^2}}, \quad \bar{y} = \frac{1}{N} \sum_{i=1}^N y_i$$

**Baseline:** Linear regression (degree = 2) w/ Latin Hypercube Sampling

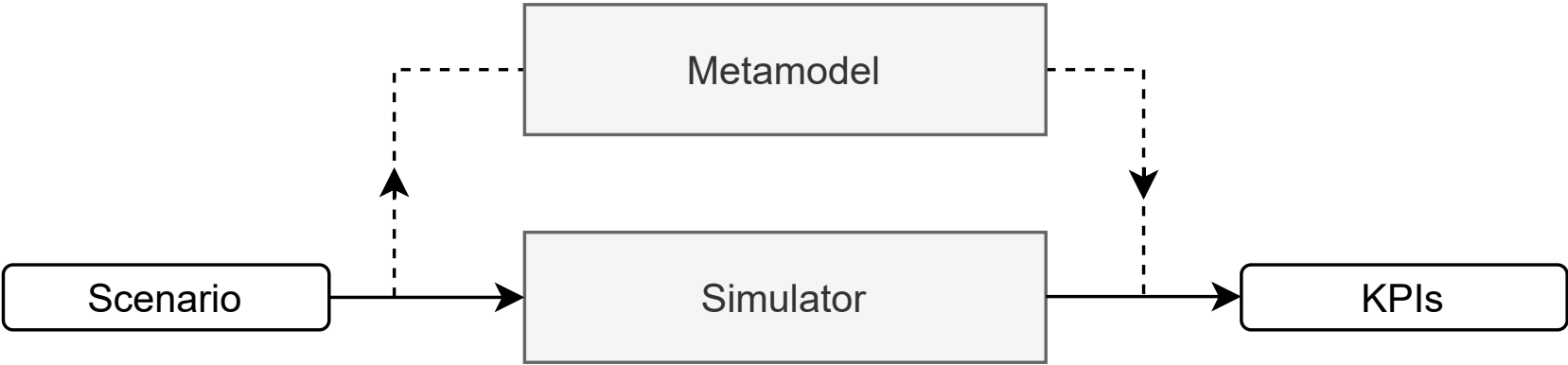
# Results



All outputs are in appendix

# Research Question

How good is this approach in terms of speed and accuracy?



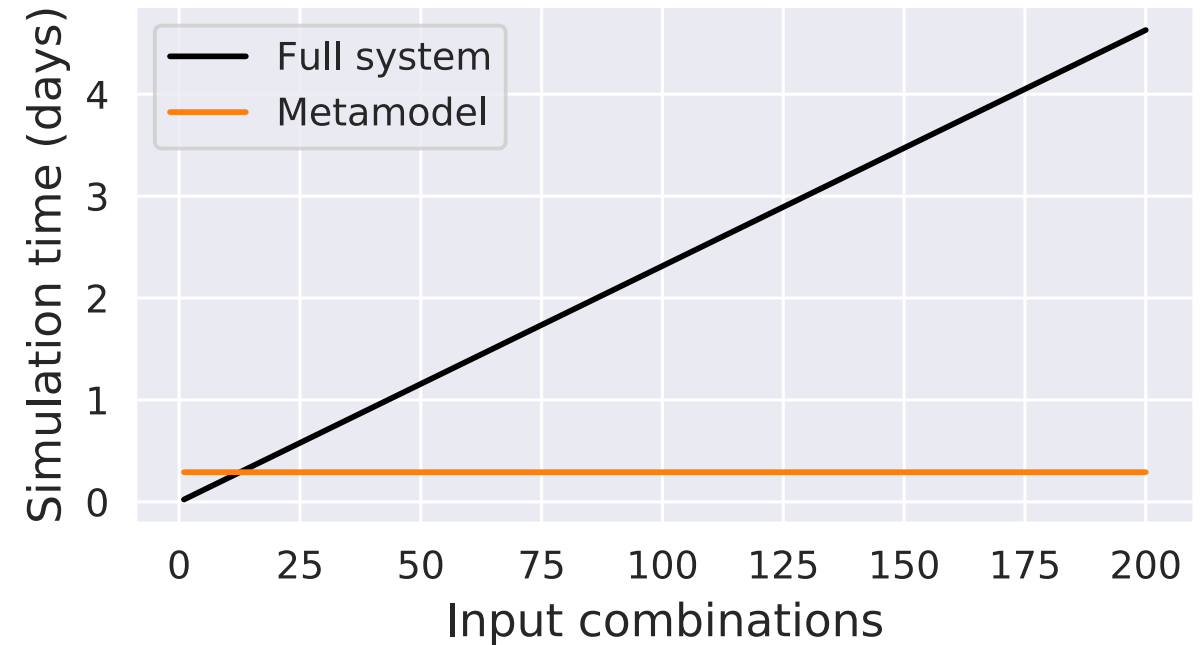
# Speed

## Full system

Explore the simulator by running it multiple times for specific scenarios (input combinations)

## Simulation time

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

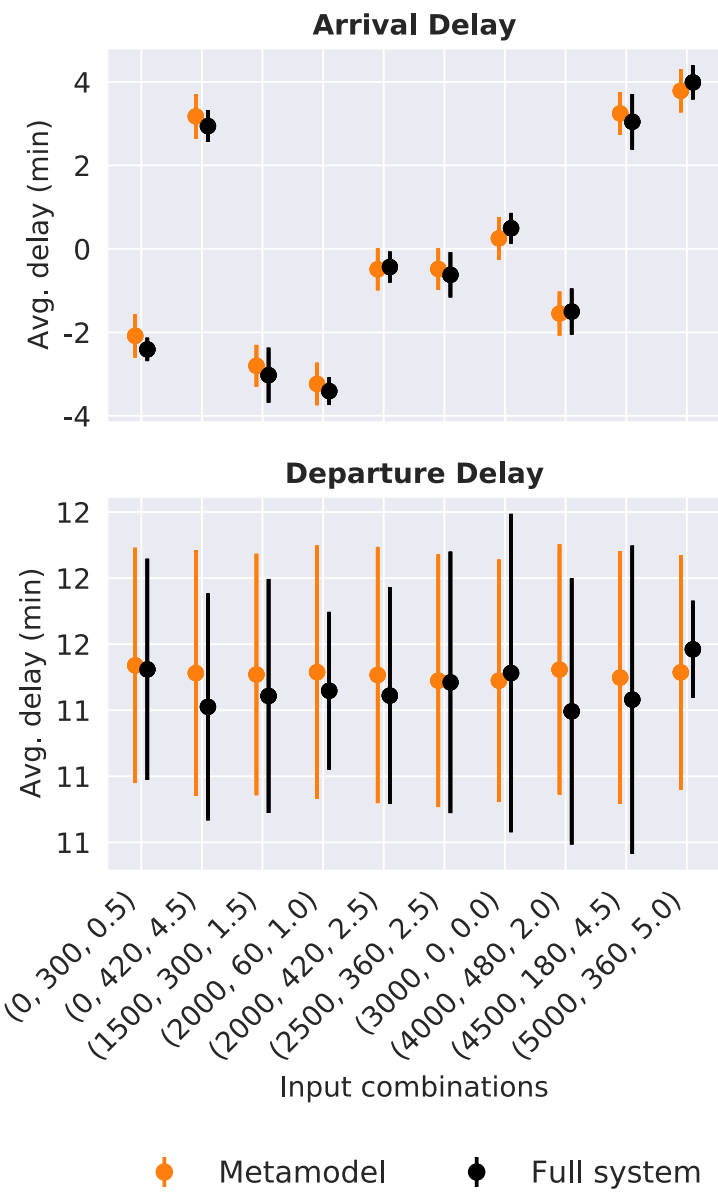


# Accuracy

## Evaluation

Get mean and standard deviation from the full system directly from the 10 simulations.

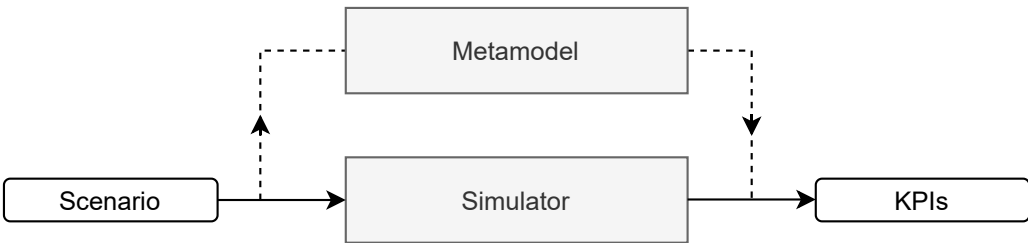
- 1) The mean predictions from the metamodel.
- 2) The coverage of the confidence intervals.



All outputs are in appendix

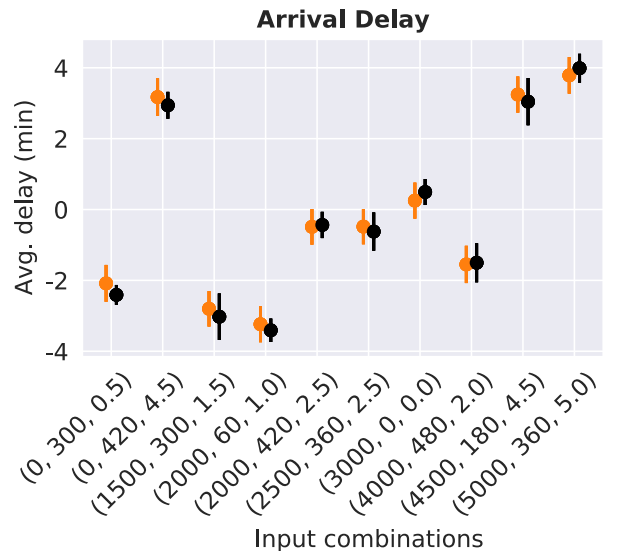
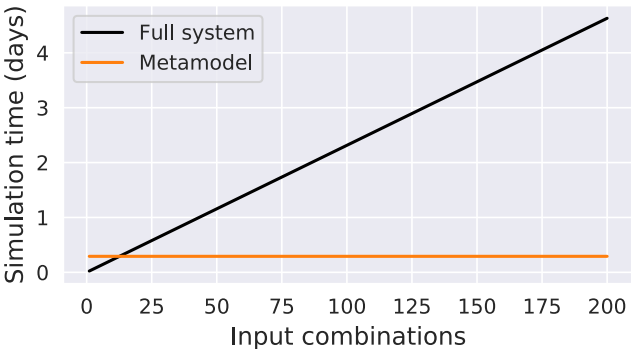
# Conclusion

Can we bypass the expensive simulator with another model? YES!



What does this mean from a policy perspective? We can do...

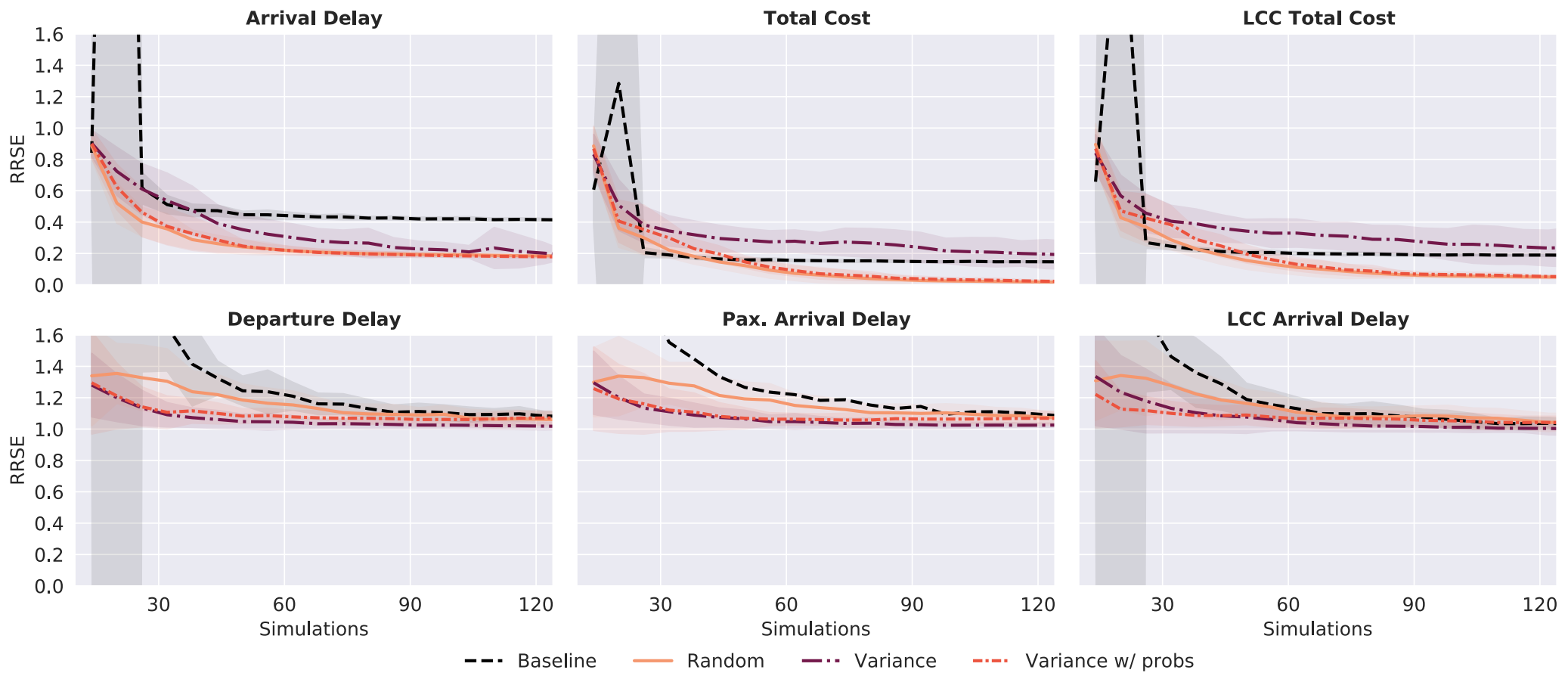
- A more comprehensive policy analysis in the same time
- The 'original' policy analysis in a shorter time
- Policy analyses that otherwise would be infeasible to do in practice due to long simulation times



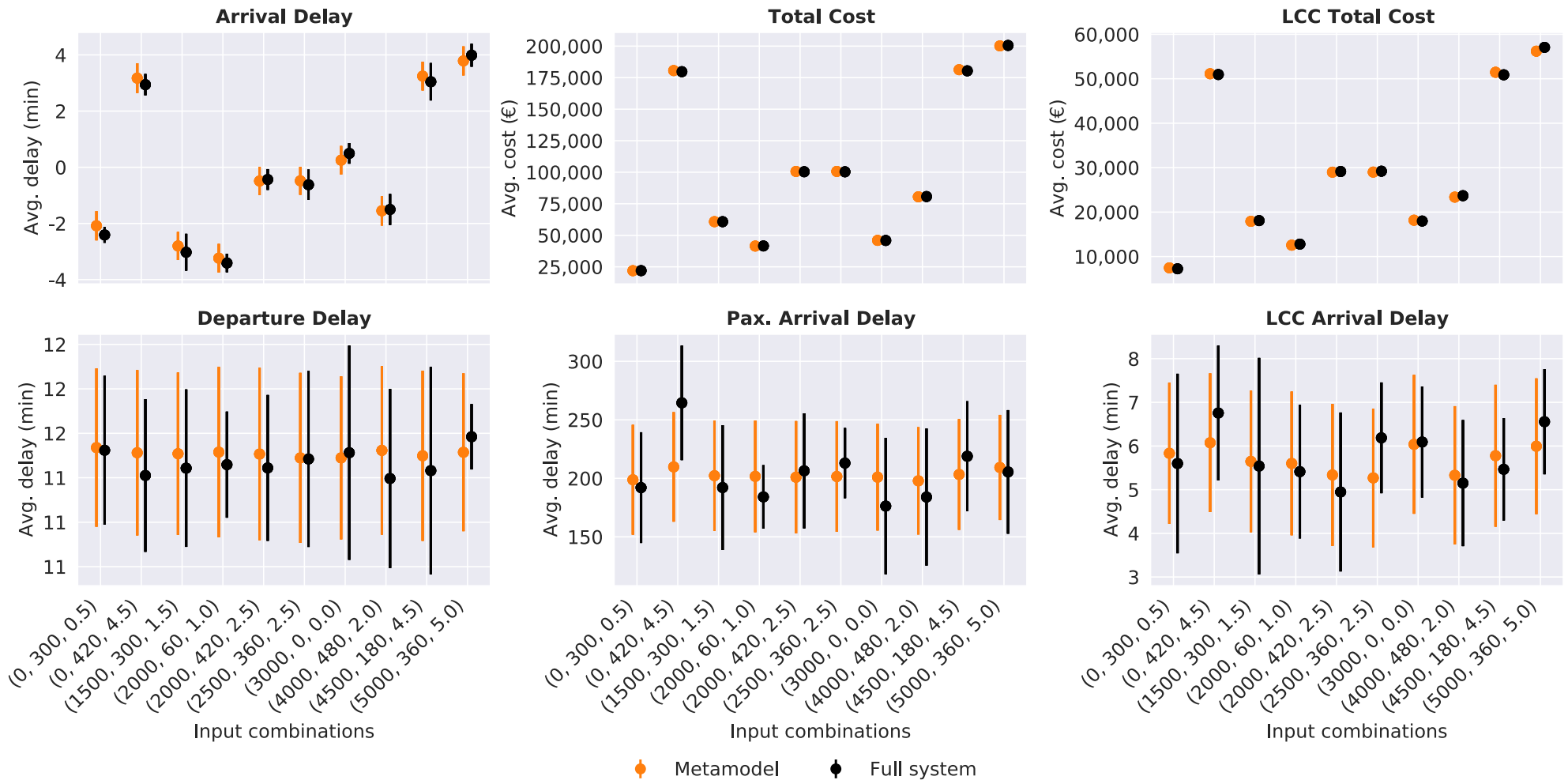
# Questions?

Contact: [chrrii@dtu.dk](mailto:chrrii@dtu.dk)

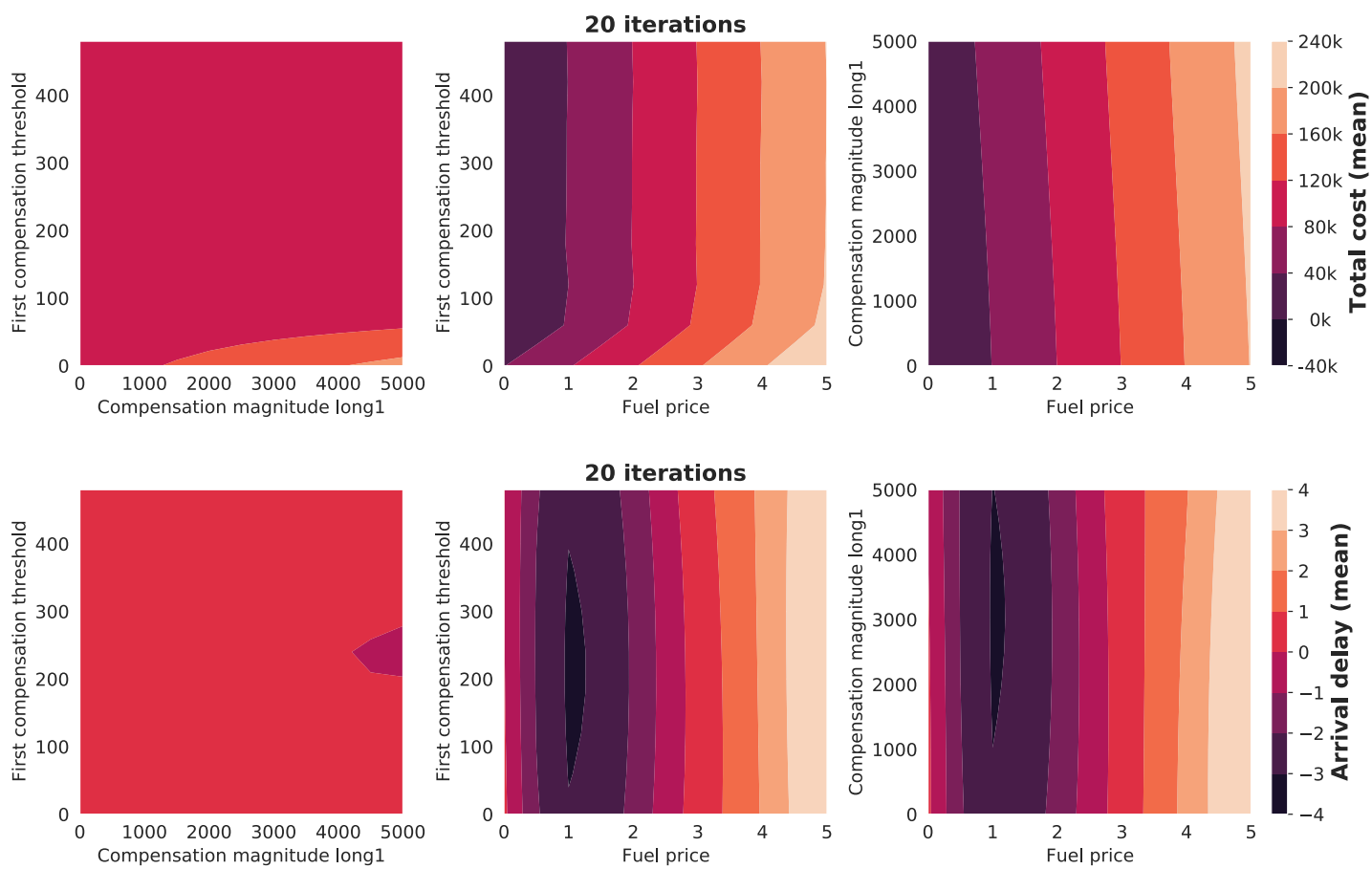
# Appendix: Results



# Appendix : Accuracy



# Appendix: Explore simulator



# Appendix: Active Learning with Metamodeling

