Safety Evaluation of Vehicle Automation Using Counterfactual Simulations

Xiaomi Yang

Department of Mechanics and Maritime Sciences, Chalmers University of Technology, Sweden

Facilitate safety performance improvements of conflict and crash avoidance systems by using computational driver models through a) the development of improved comfort zone-based crash avoidance systems, and b) improving safety assessment methods that use driver behavior models by developing efficient sampling methods.

BACKGROUND

- Virtual safety assessment is critical in the safety benefit assessment of conflict and crash avoidance systems.
- Scenario-based safety assessment plays an important role in the safety benefit evaluation of conflict and crash avoidance systems
- A massive amount of simulation is needed to generate representative critical cases.
- Several research gaps (i.e., opportunities to improve the simulation processes and guidance on when the experiments could stop) across the virtual simulation chain and experiment processes

COUNTERFACTUAL SIMULATION

- Counterfactual simulation simulates what could have happened if there were conflict and crash avoidance systems in original/historic crashes.
- The average safety performance of AEB including driver's comfortable braking and steering (65%; CAEB algorithms) is higher than traditional/basic required-deceleration-based AEB (47%; BAEB).

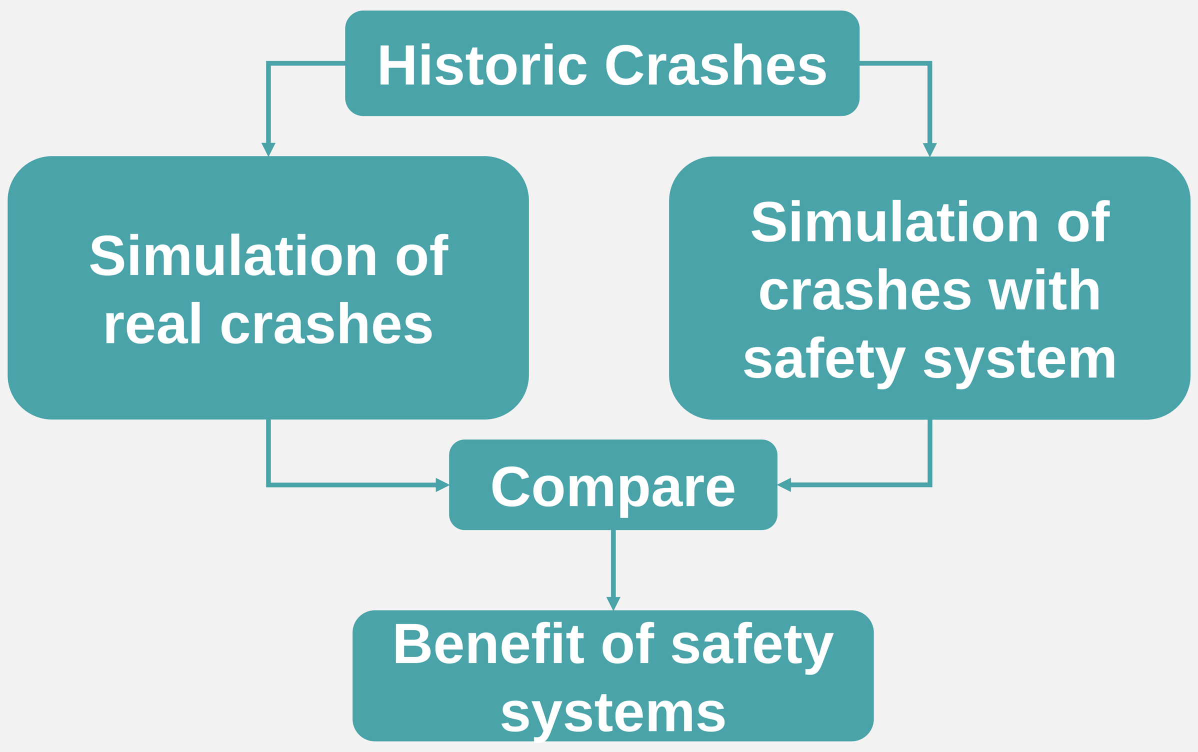

Fig1: Counterfactual simulation for safety assessment.

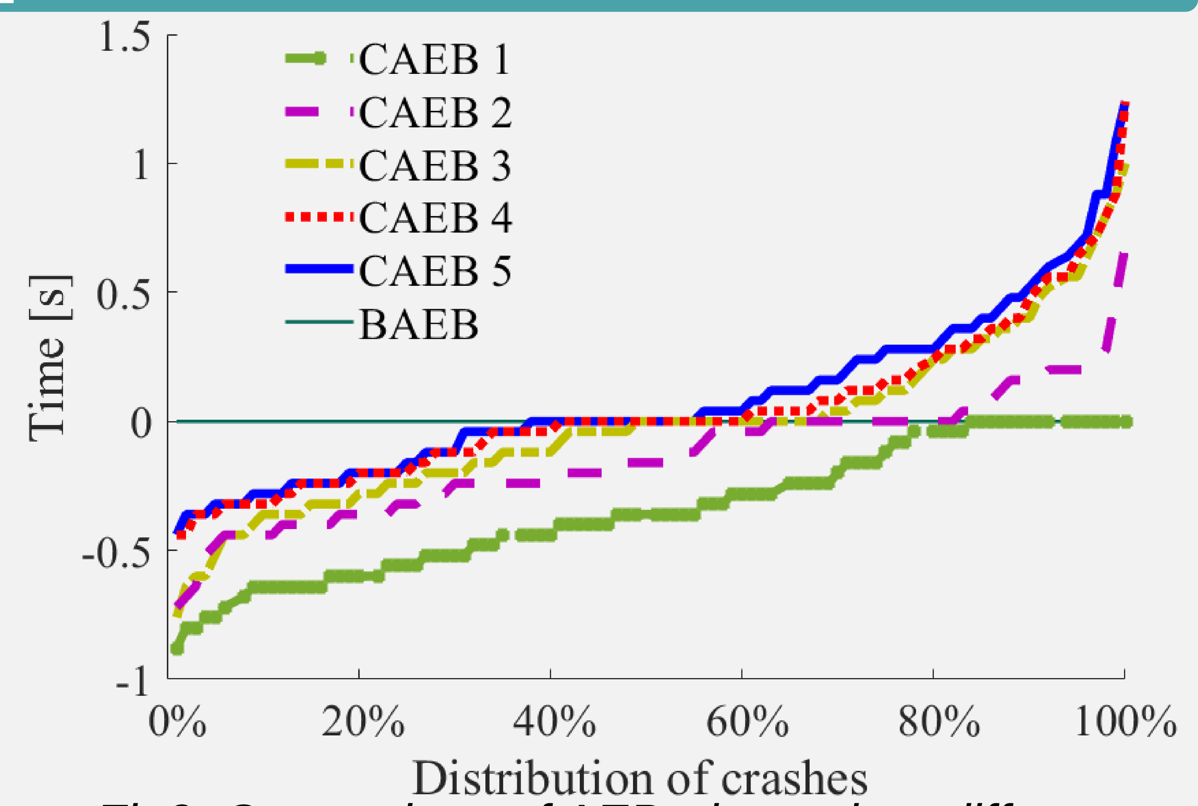

Fig2: Comparison of AEB trigger time differences.

ACTIVE SAMPLING

- Active sampling -> machine learning-assisted optimal subsampling method.
- Update sampling scheme at each iteration and stop when predefined target precision is reached.
- Active sampling outperforms simple random sampling and importance sampling.

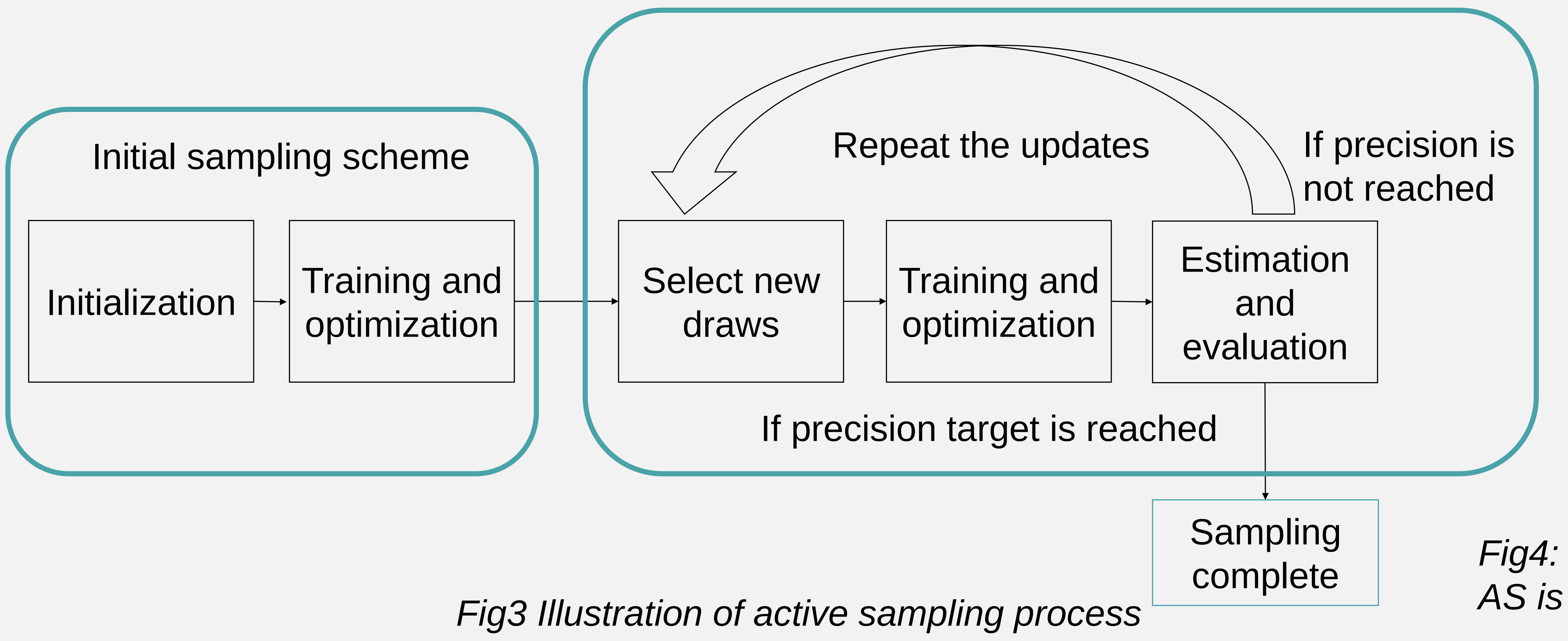

Fig3 Illustration of active sampling process

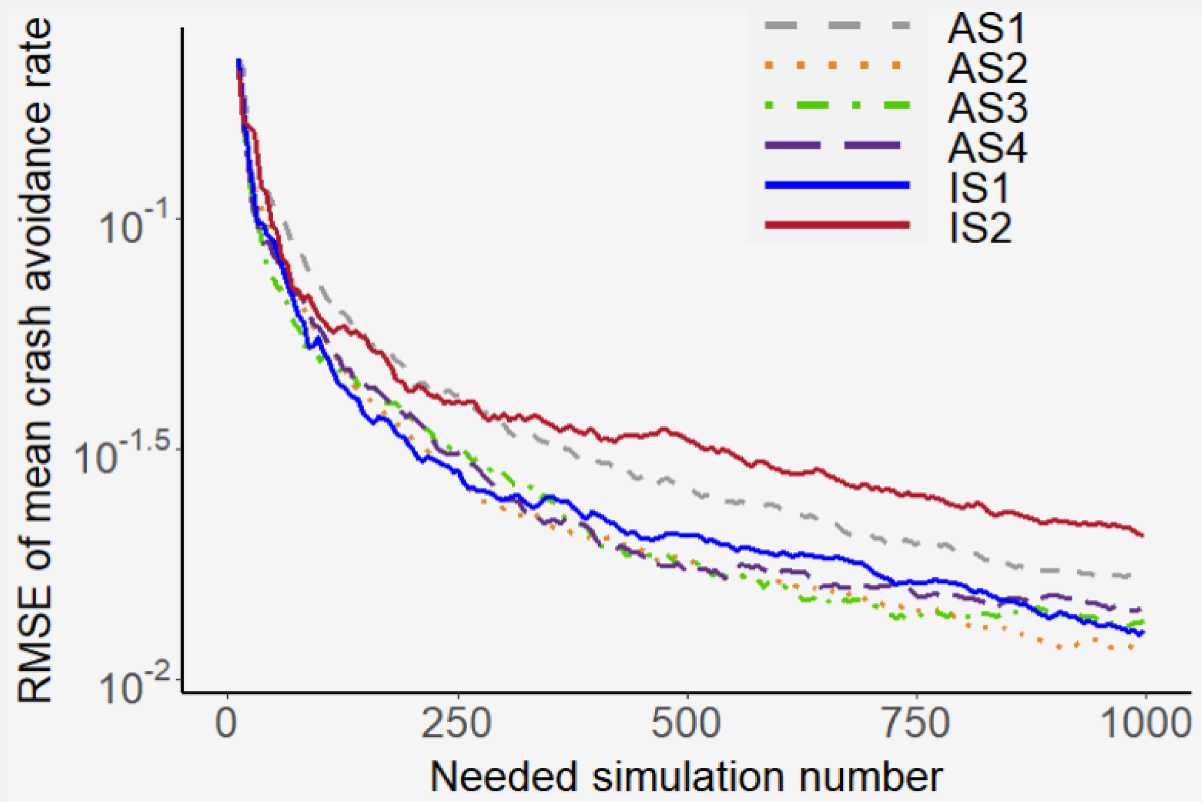

Fig4: RMSE of crash avoidance rate for different sampling methods. AS is active sampling and IS is importance sampling.

BAYESIAN POWER PREDICTION

- "Rehearsal simulations" – what may happen if experiment continues? Predictive data generation using posterior distributions.
- Stop when collected enough data or likely not able to collect enough data in the future within available resources.

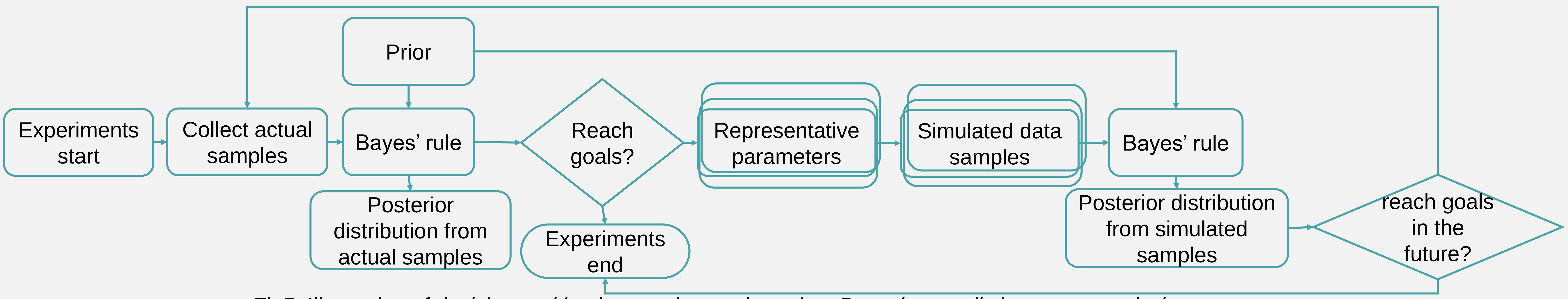

Fig5: Illustration of decision-making in experiments based on Bayesian predictive power analysis

LATEST PUBLICATION & CONTACT

- *Yang, X., Lubbe, N., & Bärgman, J. (2022). Different automated emergency braking algorithm designs result in similar residual crash characteristics: Virtual benefit assessment of AEB for car-to-two-wheeler crashes in China. IET Intelligent Transport Systems, submitted.*
- *Imberg, H., Yang, X., Flannagan, C., & Bärgman, J. (2022). Active sampling: A machine-learning-assisted framework for finite population inference with optimal subsamples. arXiv preprint arXiv:2212.10024.*
- *Yang, X. (2023). Safety Evaluation Using Counterfactual Simulations: The Use of Computational Driver Behavior Models in Crash Avoidance Systems and Virtual Simulations with Optimal Subsampling (Doctoral Licentiate thesis, Chalmers Tekniska Hogskola; Sweden)).*

Supervisors:
Jonas Bärgman (Chalmers University of Technology)
Carol Flannagan (University of Michigan Transportation Research Institute)
Contact Details:
jonas.bargman@chalmers.se
cacf@umich.edu
xaiomi.yang@chalmers.se

SHAPE-IT

CHALMERS

This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement 860410