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# SIMULATION-OPTIMIZATION CONFIGURATIONS FOR FUGITIVE INTERCEPTION

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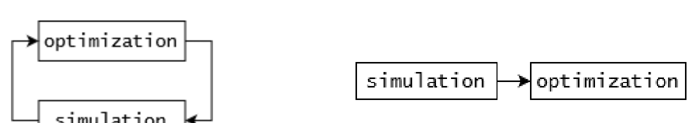
## ABSTRACT

Simulation-optimization can be used to support near-real-time decision-making, but timely calculation of the solution is essential. Besides increasing computation power and algorithm efficiency, the configuration in which simulation and optimization are combined can reduce the computation time of simulation-optimization of large problems. We compare two configurations using a fugitive interception problem and show the potential of sequential simulation-optimization to mitigate the expensive optimization of simulation models.

## 1 INTRODUCTION

The police need operational support to intercept fleeing criminals. This is complex due to the unpredictability of the fleeing criminal, the many possible interception strategies, and limited decision-making time. Simulation-optimization can support the decision-making by suggesting solutions. The timely calculation of these solutions is essential but challenging due to the complexity of the problem. Approaches to ensure timely computation primarily address two factors: (1) the number of function evaluations needed by the optimization engine to find the solution, which can be reduced by improvements of optimization algorithms for simulation-optimization to handle the rugged fitness landscape; and (2) the computation time per function evaluation, which can be reduced by increasing computation power or training surrogate models.

A less explored approach is the implementation of different simulation-optimization configurations. Figueira and Almada-Lobo (2014) distinguish four configurations of simulation-optimization, of which our paper examines two: (1) simulation model optimization (Figure 1a): the configuration most commonly understood as *simulation-optimization* (Fu 1994). A simulation model evaluates the decision variables proposed by an optimization algorithm to find the values that maximize or minimize the simulation model's output. This configuration requires repetitive evaluation of the simulation model. (2) sequential simulation-optimization (Figure 1b): the output of a Monte Carlo simulation model describes (part of) the constraints of an optimization model. The simulation model is only evaluated once for a set number of replications. Therefore, we expect the computation time to be more manageable for large simulation-optimization problems compared to simulation model optimization.




(a) Simulation model optimization (b) Sequential simulation-optimization

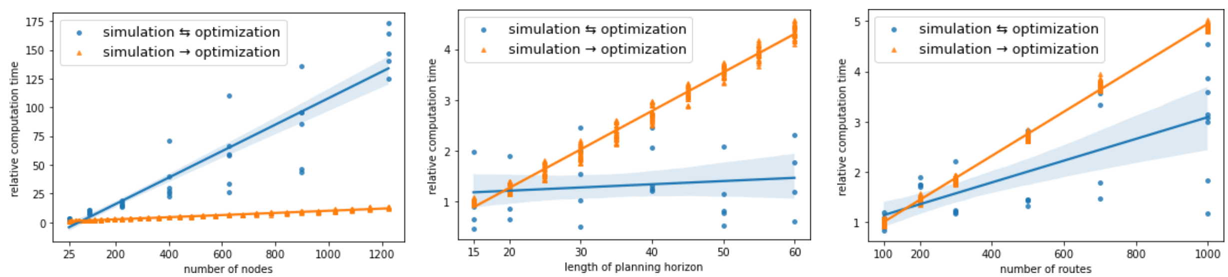
Figure 1: Simulation-optimization configurations examined in this paper, adapted from (Figueira and Almada-Lobo 2014).

We implement both configurations for a fugitive interception problem, a special case of the Flow Interception Problem (Hodgson 1990), which determines the best positions of facilities to maximize the intercepted flows. We examine the scaling of the two implementations with increasing problem size.

## 2 RESULTS

We vary three parameters to create problems of various sizes: the number of nodes in the graph (Figure 2a), the length of the planning horizon (Figure 2b), and the number of plausible routes considered for the fugitive (Figure 2c), and record the relative computation time.

Compared to sequential simulation-optimization, the computation time of simulation model optimization increases rapidly with an increasing number of nodes due to the increase in possible values for the decision variable and consequent increase in required evaluations of the simulation model. Simulation model optimization scales more favorably than sequential simulation-optimization in the other dimensions, where only the complexity of the simulation model increases. However, this difference is insignificant in light of the increase in computation time with an increasing number of nodes. Therefore, sequential simulation-optimization is a promising approach to reduce the optimization time of complex simulation models when the problem can be separated into simulated (uncontrollable) and optimized (controllable) components, especially when many possible values for the decision variables exist.




(a) Number of nodes (b) Length of planning horizon (c) Number of escape routes

Figure 2: Scaling of relative computation time of simulation model optimization (blue) and sequential simulation-optimization (orange). Computation time is scaled so that the computation time of the smallest experiment is equal to 1. The default values are: number of nodes: 625; length of planning horizon: 30; number of escape routes: 500. The shaded area represents the 95% confidence interval. Note that the vertical axes are different across the subfigures.

## 3 CONCLUSION

Simulation-optimization can support near-real-time decision-making. To be useful for near-real-time decision-making, timely calculation of the solution is essential. Besides increasing computation power and algorithm efficiency, the choice of simulation-optimization configuration can reduce the computation time of simulation-optimization of large, complex problems. Sequential simulation-optimization is a promising approach to mitigate the expensive optimization of complex simulation models. Timely optimization is especially important in (near) real-time decision-making, but this paper addresses the broader problem in simulation-optimization of finding good solutions for complex simulation models. The main avenues for further research are examining the relative scaling of computation time for other models, simulation software, and optimization algorithms.

## REFERENCES

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