Quasi-OTEE versus Kriging-based approach for the sensitivity analysis of computationally expensive traffic simulation models: an exploratory study

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Introduction

Sensitivity Analysis (SA) is widely used in the calibration of traffic simulation models: it provides the modeler better knowledge about the relationship between model inputs and outputs, so the calibration can focus on the most important parameters. However, when the model is computationally expensive and has many parameters, many SA techniques (e.g., Monte Carlo approaches) are unfeasible due to the high computational cost.

Quasi-OTEE [1] and the Kriging-based approach [2] are two recently developed methods for the SA of computationally expensive traffic simulation models. In this study, we aim at comparing these two methods and better understanding their advantages and disadvantages.

Methodology

Quasi-OTEE Method

The quasi-OTEE method is a general screening approach based on the Elementary Effects (EE) method [3] but with higher efficiency. The sensitivity information is derived by calculating the Sensitivity Indexes (i.e., μ^*, μ and σ of EE) via sampling with the Morris random trajectories. The efficiency can be enhanced by using the Optimized Trajectories (OT), a subset of the Morris trajectories with the largest dispersion in the input space [3]. The quasi-Optimized Trajectories (quasi-OT) in [1] improves the original OT [3] and greatly reduces the computational cost in OT selection. The case study provided in [1] demonstrated that the quasi-OTEE approach can properly identify the most influential parameters from a computationally expensive model.

Kriging-based Method

Kriging or Gaussian-process meta-models extend the Kriging principles of geo-statistics to any experimental science by considering the correlation between two different samples (real or model-derived) depending on the distance between input variables. Numerous studies have shown that this interpolating model provides a powerful statistical framework for computing an efficient predictor of model response [2]. In the present method, a Kriging approximation of the model to analyze is estimated until it satisfies some accuracy criteria. Then using it, variance-based sensitivity indices (Saltelli formulas) are calculated in a Monte Carlo framework, using Sobol sequences or quasi-random numbers. Since meta-model evaluations are fairly inexpensive, the size of the Monte Carlo experiment can be very high, ensuring numerical convergence of the sensitivity indices.

Case Study

Traffic Model: AIMSUN 7 meso

Network Layout: Urban network (10km extension, 91 OD pairs)

Inputs to the Sensitivity Analysis: 3 experiment parameters (seed, rT, rTs), 3 vehicle parameters (mA, vL, gWt), 1 network parameter (jD); and 1 model input (OD)

Model Outputs: traffic flow, density, travel time, and delay over the whole network and over 8 individual sections

Total Runs of the Model: 450 (quasi-OTEE), 512 (Kriging-based approach), 40'960 (variance-based approach, used as reference)
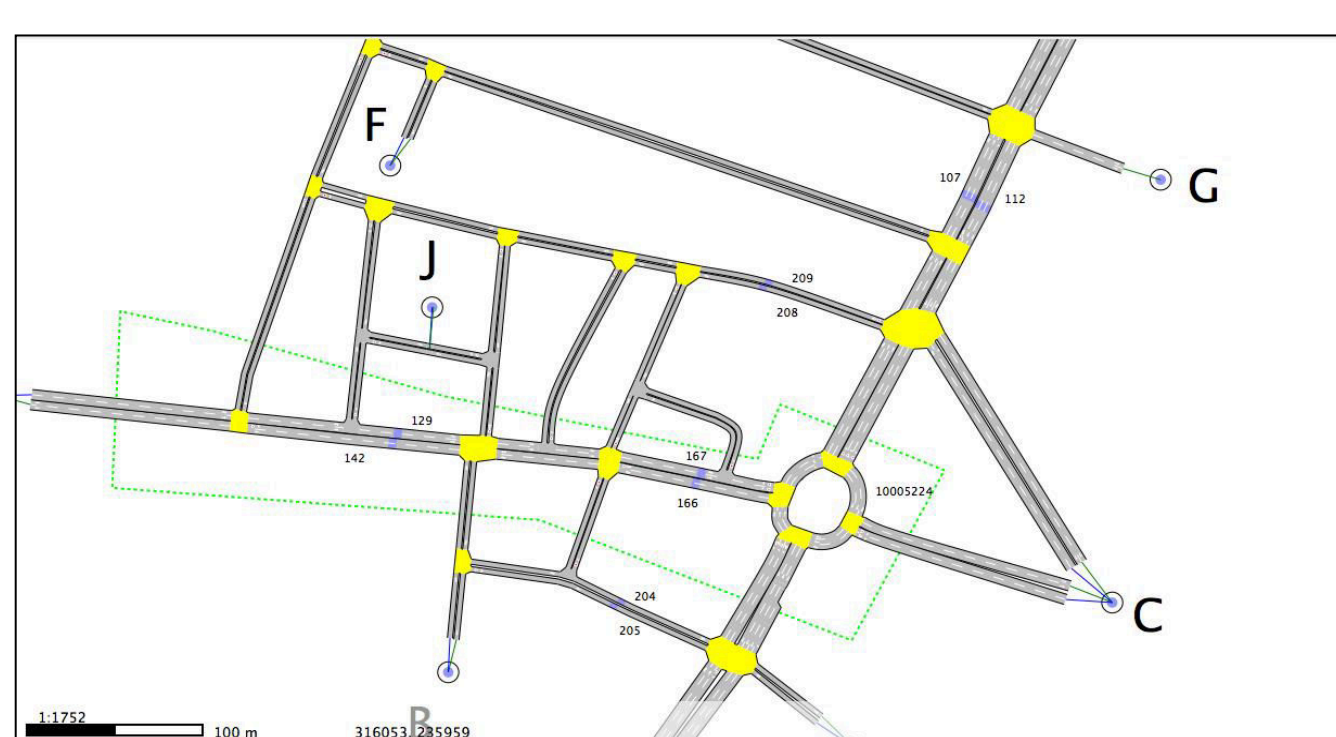
Parameter	Range	Units	Type
Reaction Time (rT)	[0.5, 2]	seconds	continue
Reaction Time Stop (rTs)	[0.5, 3]	seconds	continue
Vehicle Length (vL)	[4, 8]	meters	continue
Jam Density (jD)	[140, 200]	Veh/km	continue integer
Give-way Time (gWt)	[1, 50]	seconds	continue
Max acceleration (mA)	[1, 5]	m/s²	continue
Random Seed (seed)	[1, 2.2x10⁹]	--	continue integer
Demand factor (OD)	[0.75-1.25]	--	continue

The comparison of the two approaches in terms of performance is shown in the figures below. Overall, there is almost no variation in performance across types of outputs, but some variations in performance across sections. The quasi-OTEE yields less Type II errors (considering an important parameter as non-important) but more Type I errors (considering a non-important parameter as important), and hence it is better for finding the whole set of important parameters. On the other hand, the Kriging-based approach has a higher precision in ranking the important parameters and determining the most important ones.
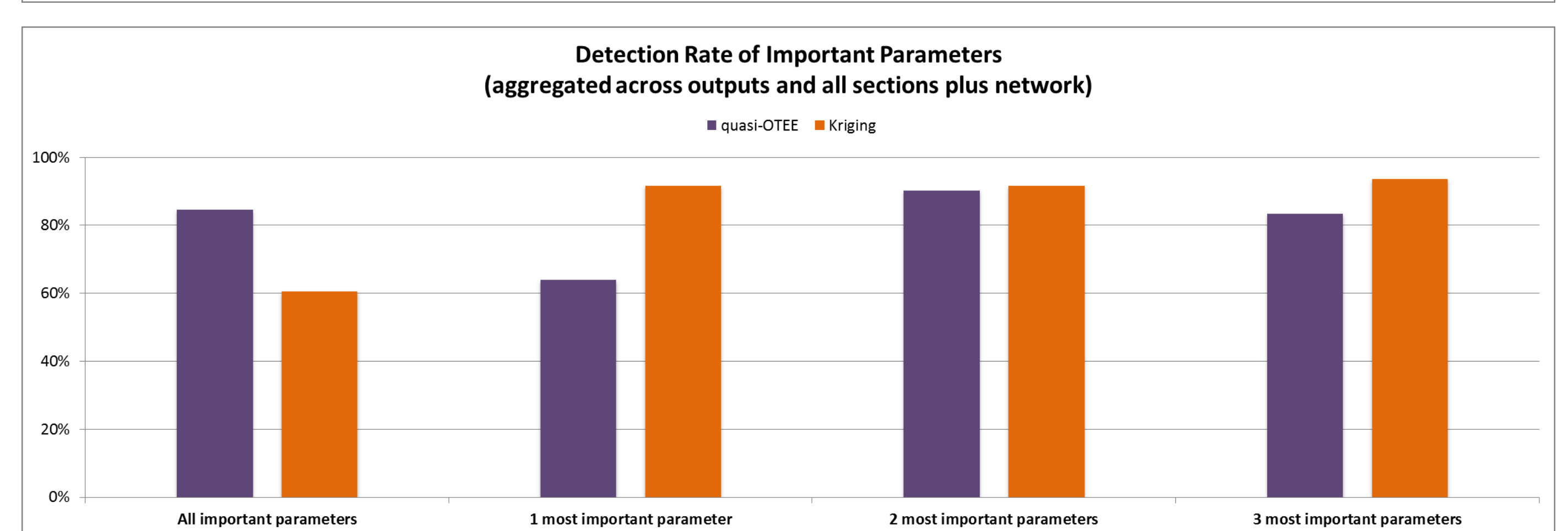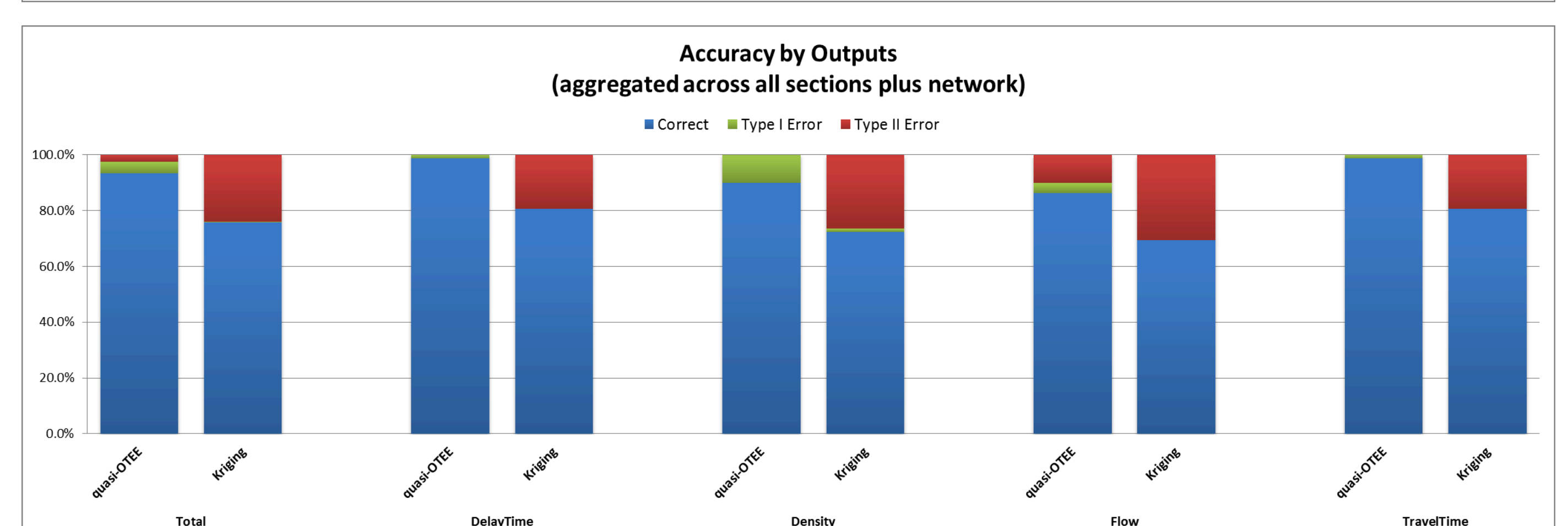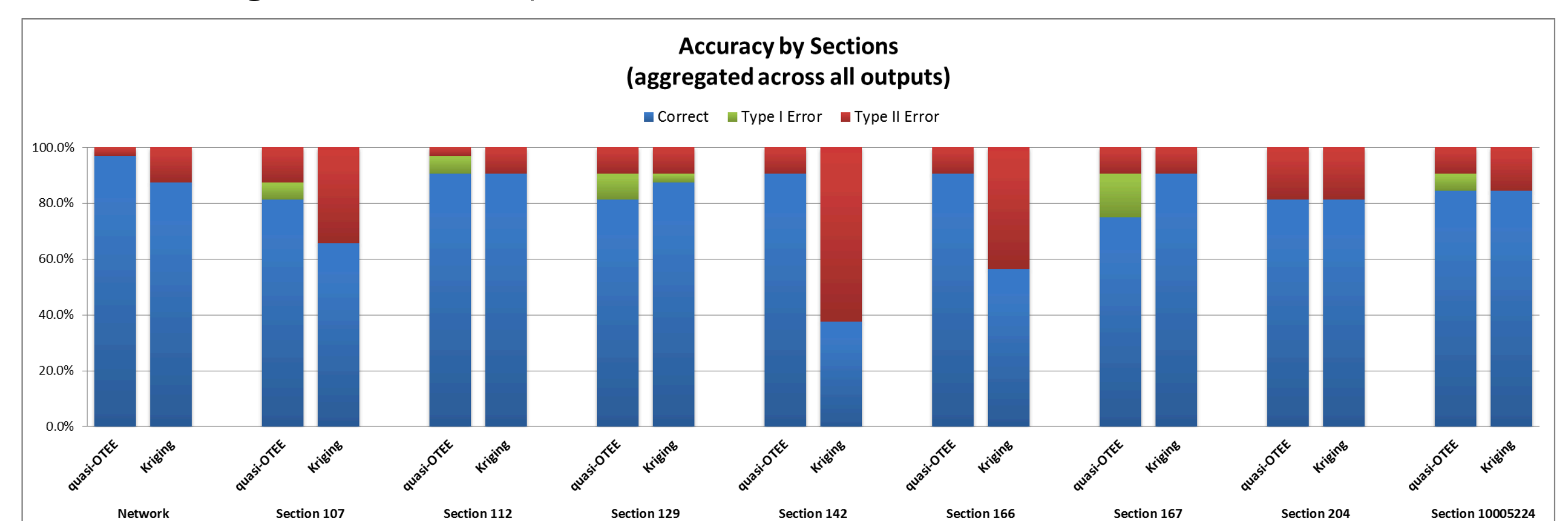
Conclusions

Preliminary results show that both methods are able to identify, to a good degree, the important parameters. The Kriging-based approach makes the model simpler; and is able to define with very high precision the ranking of the most important parameters, but at the cost of missing some high-dimensional interactions that the method does not capture. On the other hand, the quasi-OTEE approach is very robust on all types of interactions and therefore it is better in finding those parameters to discard. These findings suggest the following rule-of-thumb for the SA of computationally expensive traffic simulation models: *the quasi-OTEE SA can be used to find the important parameters, and decide which parameters to discard. Then, the Kriging-based SA can be used to refine the analysis and calculate first order indices to identify the correct rank of those important parameters*.

References

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