Efficient Quantification of Model Uncertainties When De-boarding a Train

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Abstract - It is difficult to provide live simulation systems for decision support. Time is limited and uncertainty quantification requires many simulation runs. We combine a surrogate model with the stochastic collocation method to overcome time and storage restrictions and show a proof of concept for a de-boarding scenario of a train.

Keywords: Pedestrian dynamics, uncertainty quantification, surrogate models

1. Introduction

When trying to assess whether or not the passengers of a train can safely de-board onto an already over-full platform a safety officer faces a number of uncertainties. Chief among them are the initial numbers of passengers on the train and on the platform. By varying uncertain parameters in a computer simulation, one can, in principle quantify their effect [1] as demonstrated in [2] for the evacuation of a train. One obtains probability distributions of quantities of interest, in our case, the number of passengers on the platform. If this number exceeds a threshold, the safety officer might want to evacuate the platform. Uncertainty quantification would tell how likely this event is, given the initial passenger distributions (see Fig. 1 left).

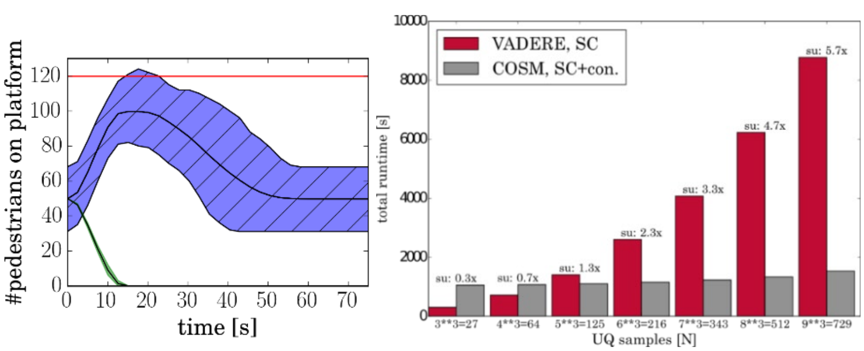

Fig. 1: Left: Mean and standard deviations of passengers on (green) and off (blue) the train. Right: total runtime of stochastic collocation for the original model compared to stochastic collocation for COSM.

With this approach, the computer scientist faces two problems: Simulation time and storage costs. Sampling the parameter space means that a usually very complex simulation program runs many times, which makes the process slow. The resulting data which includes, for example, trajectories of individual pedestrians over time is high dimensional, expensive to store and hard to retrieve from its vast storage space. For the safety officer, this means that the results come too late to act.

2. The Closed Observable Surrogate Model (COSM)

To overcome the speed and storage barriers, we propose a low dimensional surrogate model that captures the dynamic of the original data and that allows observation of the quantity of interest. Thus, one can investigate the surrogate instead of the original model. As a further plus, techniques that reduce the number of samples for uncertainty quantification [3], but depend on prior choices for the distribution of uncertain parameters, can be applied on the surrogate, without having to re-sample the original model. Stochastic collocation [4] is such a technique.

The solution we offer here, the Closed Observables Surrogate Model, is based on theoretical work in [5, 6]. It reduces storage requirements in the very costly time domain, by using time-delayed embedding of the original data to ensure that the output can be uniquely constructed. This means that we initially increase the model's dimensionality, see Fig. 3 (right). Consequently, we need to strip away redundant dimensions. For this, we employ a manifold learning technique: Diffusion Maps [7]. The reduction allows efficient storage and reloading of the surrogate model. Through interpolation, one can access data points in areas that were not simulated beforehand. Fig.2 shows how a quantity of interest, the number of passengers on a train, is computed based on the original data and on the surrogate for different uncertain parameter pairs (initial number of persons on platform; initial number of persons on train). An interpolation is constructed for (#platform; #train) = (75; 60), which matches data explicitly simulated for these initial values very well.

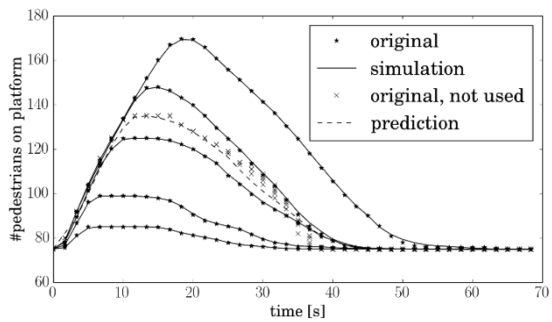

Fig. 2: Comparison of a quantity of interest (number of pedestrians on the platform) computed with the original simulation result (solid) and with the surrogate (dashed).

The next step is to combine the Closed Observables Surrogate Model with stochastic collocation [4]. The final combined method is illustrated in Fig. 3 (left). In the train example, the final combined method delivers results close to a classic Monte Carlo approach [4] that repeatedly samples the original model, and that we use as a benchmark. The new approach is much faster: Even in our small example, with only three uncertain parameters (initial number of initial pedestrians on the platform, initial number of pedestrians on the train, mean free flow velocity) we achieve a speed-up factor of about six for 9^3=27 samples. The runtime for the surrogate does not increase significantly with the number of samples (see Fig. 1 (right)).

3. Conclusion

Fast and cheap surrogate models to reproduce simulation data or measured data are constructed using time delayed embedding for uniqueness and diffusion maps for subsequent order reduction. The gain in speed and storage efficiency allows studying the effect of uncertain parameters on safety relevant quantities of interest, such as the number of passengers in a critical location. Stochastic collocation further reduces the number of samples. With the combined speed-up we come closer to the goal of supporting decision making in a live situation. We presented a sample application as proof of concept. To be useful to end users, the methods, which are not trivial to implement, must be made accessible through libraries and frameworks.

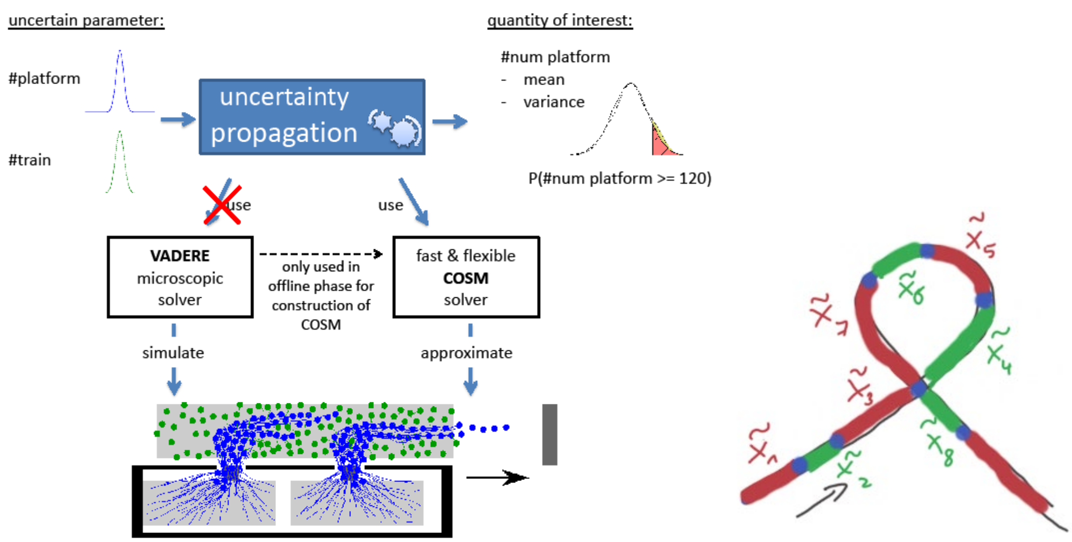

Fig. 3: Left: Simulation of the de-boarding process, and uncertainty quantification, including the construction of a surrogate model. Right: Illustration of time-delayed embedding to recover uniqueness of a dynamic on a string.

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References

[1] Iaccarino, G., “Quantification of uncertainty in flow simulations using probabilistic methods, “ Report on *VKI Lecture Series*, Sept. 8-12, pp. 1-30, 2008.

[2] Von Sivers I. et al., “Modelling social identification and helping in evacuation simulation,” *Safety Science*, vol. 89, pp. 288-300, 2016.

[3] Smith, R.C., “Uncertainty Quantification: Theory, Implementation, and Applications,” *SIAM Computational Science and Engineering*, 2014.

[4] Xiu, D. and Karniadakis, G.E., “The Wiener–Askey polynomial chaos for stochastic differential equations,” *SIAM Journal on Scientific Computing*, vol. 24(2), pp.359–718, 2002.

[5] Dietrich et al., “Numerical model construction with closed observables,” *SIAM Journal on Applied Dynamical Systems*, vol. 15, pp. 2078-2108, 2016.

[6] Dietrich et al., “Fast and flexible uncertainty quantification through a data driven surrogate model,” *International Journal of Uncertainty Quantification*, vol. 8, pp. 175-192 2018.

[7] Coifman, R.R. and Lafon, S., “Diffusion maps, Applied and Computational Harmonic Analysis,” vol. 21(1), pp. 5-30, 2006.