2010 NSF Workshop on Simulation Optimization

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Contact

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Career Research Interests

Probabilistic and statistical aspects of simulation experiments: random-variate generation, input modeling, output analysis, variance reduction, stochastic (black-box) root finding, and stochastic (black-box) optimization.

Optimization Research Interests

1. Local solutions of black-box root finding and optimization problems. At the 1991 WSC, Lee Schruben (with Kevin Healy) presented "Retrospective Simulation Response Optimization". During that talk, I became interested in algorithms that solve a sequence of sample-path problems, each with increasing sample size and decreasing solution error. Maybe inappropriately, I have referred to such algorithms as being *retrospective*. The design intent is to "zoom in" on the solution, as if falling from the sky onto the solution; small sample sizes correspond to being high (and therefore seeing a long distance) with no detail visible (and therefore no need to solve to much accuracy). Each problem in the sequence is solved efficiently by using the solutions to the previous problems; if there is no such efficiency, then a retrospective algorithm is not the appropriate algorithm.

Four relevant Ph.D. theses.

Honggang Wang, *Retrospective Optimization of Discrete Stochastic Systems using Simplicial Linear Interpolation*, 2009.

Raghu Pasupathy, *Stochastic Root Finding via Retrospective Approximation*, 2005.

Jihong Jin, *Retrospective Optimization of Stochastic Systems,* 1998.

Hui-Fen Chen, *Stochastic Root Finding in System Design*, 1994.

Eleven relevant papers.

K. Healy and L.W. Schruben. Retrospective simulation response optimization. Proceedings of the Winter Simulation Conference, 1991, 901–906.

R. Pasupathy and B.W. Schmeiser. Retrospective-approximation algorithms for the multidimensional stochastic root-finding problem. *ACM Trans. Model. Comput. Simul* 19 (2009).

Honggang Wang and B. Schmeiser. Discrete stochastic optimization using linear interpolation. Proceedings of the Winter Simulation Conference, 2008, 502–508.

R. Pasupathy and B. Schmeiser. Retrospective approximation algorithms for the multidimensional stochastic root-finding problem. *Proceedings of the Winter Simulation Conference*, (R.G. Ingalls, M.D. Rossetti, J.S. Smith, and B.A. Peters, eds.), 2004, 520–528.

R. Pasupathy and B. Schmeiser. Some issues in multivariate stochastic root finding. *Proceedings of the Winter Simulation Conference*, (S. Chick, P.J. Sanchez, D. Ferrin, and D.J. Morrice eds.), 2003, 574–577.

J. Jin and B. Schmeiser. Simulation-based retrospective optimization of stochastic systems: A family of algorithms. *Proceedings of the Winter Simulation Conference*, (S. Chick, P.J. Sanchez, D. Ferrin, and D.J. Morrice eds.), 2003, 543–547.

H. Chen and B. Schmeiser. Stochastic root finding via retrospective approximation. *IIE Transactions* **33** (2001), 259–275 (Special issue of *Operations Engineering* honoring Alan Pritsker).

H. Chen and B. Schmeiser. Monte Carlo estimation for guaranteed-coverage nonnormal tolerance intervals. *Journal of Statistical Computation and Simulation,* **51**(1995), 223–238. Errata: **53** (1997), U1–U2.

H. Chen and B. Schmeiser. Stochastic root finding: Problem definition, examples, and algorithms. *Proceedings of the Third Industrial Engineering Research Conference*, (ed. L. Burke and J. Jackman), 1994, 605–611.

H. Chen and B. Schmeiser. Retrospective approximation algorithms for stochastic root finding. *Proceedings of the Winter Simulation Conference*, (J. Tew, S. Manivannan, D. Sadowski, and A. Seila, eds.) 1994, 255–261.

H. Chen and B. Schmeiser. Monte Carlo estimation for guaranteed-coverage nonnormal tolerance intervals. *Proceedings of the Winter Simulation Conference*, 1993, 509–515.

2. Gradient estimation using a single point. The idea is to use information available for free when factors have random realizations, such as the observed arrival rate differing from the true arrival rate.

   Jamie Wieland, *Stochastic Gradient Estimation Using a Single Design Point*, 2007.

   J. Wieland and B. Schmeiser. Stochastic gradient estimation using a single design point. Proceedings of the Winter Simulation Conference, 2006, 390–397.

   J. Wieland and B. Schmeiser. Derivative estimation with known control-variate variances. Proceedings of the Winter Simulation Conference, 2007, 560–567.

3. The development of DARTS, a family of prospective root-finding (and maybe eventually optimization) algorithms for finding local solutions. The design idea is smarter stochastic approximation, both in terms of the next solution value and in terms of dynamic sample sizing (with Raghu Pasupathy).

4. The initial-transient problems associated with solutions of root-finding and optimization algorithms. Here the time-series data have both initial bias and variance that is asymptotically zero. This is the same problem as deciding which point estimator to report to the user (with Raghu Pasupathy).

5. How to indicate sampling error to the user (with Raghu Pasupathy).