

MNMUQ 2019 Summer School

Modeling and Numerical Methods for Uncertainty Quantification

Suggested readings

Contents

1	Monday (September 2, 2019)	2
1.1	Introduction to simulation methods (C. Proppe)	2
1.2	Variance reduction, importance sampling (J.-M. Bourinet)	2
1.3	Subset simulation (I. Papaioannou)	3
1.4	Multilevel Monte Carlo (C. Proppe)	3
2	Tuesday (September 3, 2019)	4
2.1	Introduction to random processes (F. Poirion)	4
2.2	Random processes: identification and simulation (F. Poirion)	4
2.3	Polynomial chaos expansion (B. Sudret)	5
2.4	Sparse polynomial chaos expansion (B. Sudret)	5
3	Wednesday (September 4, 2019)	6
3.1	Low-rank approximation (M. Chevreuil)	6
3.2	Support vector machines (J.-M. Bourinet)	6
3.3	Kriging (R. Le Riche)	7
3.4	Global sensitivity analysis (B. Iooss)	7
4	Thursday (September 5, 2019)	8
4.1	Optimization under uncertainty (R. Le Riche)	8
4.2	Structural health monitoring (J. Goulet)	8
5	Friday (September 6, 2019)	9
5.1	Inverse methods (B. Rosić)	9
5.2	Bayesian updating (I. Papaioannou)	9

1 Monday (September 2, 2019)

1.1 Introduction to simulation methods (C. Proppe)

1. Au S.-K., Beck J.L. (2001). Estimation of small failure probabilities in high dimensions by subset simulation. *Probabilistic Engineering Mechanics*, 16(4), pp. 263–277.
2. Cérou F., Del Moral P., Furon T., Guyader A. (2012). Sequential Monte Carlo for rare event estimation. *Statistics and Computing*, 22(3), pp. 795–808.
3. Proppe C. (2008). Estimation of failure probabilities by local approximation of the limit state function. *Structural Safety*, 30(4), pp. 277–290.
4. Proppe C., Pradlwarter H.J., Schuëller G.I. (2003). Equivalent linearization and Monte Carlo simulation in stochastic dynamics. *Probabilistic Engineering Mechanics*, 18(1), pp. 1–15.
5. Walter C. (2015). Moving particles: a parallel optimal multilevel splitting method with application in quantiles estimation and meta-model based algorithms. *Structural Safety*, 55, pp. 10–25.

1.2 Variance reduction, importance sampling (J.-M. Bourinet)

1. Bourinet J.-M. (2018a). Reliability analysis and optimal design under uncertainty – Focus on adaptive surrogate-based approaches. HDR Report. Université Clermont Auvergne, France. See Chapter I: Rare-event probability estimation.
2. Dubourg V., Sudret B., Deheeger F. (2013). Metamodel-based importance sampling for structural reliability analysis. *Probabilistic Engineering Mechanics*, 33, pp. 47–57.
3. Geyer S., Papaioannou I., Straub D. (2019). Cross entropy-based importance sampling using Gaussian densities revisited. *Structural Safety*, 76, pp. 15–27.
4. Kurtz N., Song J. (2013). Cross-entropy-based adaptive importance sampling using Gaussian mixture. *Structural Safety*, 42, pp. 35–44.
5. Morio J. (2012). Extreme quantile estimation with nonparametric adaptive importance sampling. *Simulation Modelling Practice and Theory*, 27, pp. 76–89.
6. Papaioannou I., Papadimitriou C., Straub D. (2016). Sequential importance sampling for structural reliability analysis. *Structural Safety*, 62, pp. 66–75.

1.3 Subset simulation (I. Papaioannou)

1. Au S.-K., Beck J.L. (2001). Estimation of small failure probabilities in high dimensions by subset simulation. *Probabilistic Engineering Mechanics*, 16(4), pp. 263–277.
2. Au S., Wang Y. (2014). *Engineering risk assessment with subset simulation*. John Wiley & Sons.
3. Botev Z.I., Kroese D.P. (2012). Efficient Monte Carlo simulation via the generalized splitting method. *Statistics and Computing*, 22(1), pp. 1–16.
4. Cérou F., Del Moral P., Furon T., Guyader A. (2012). Sequential Monte Carlo for rare event estimation. *Statistics and Computing*, 22(3), pp. 795–808.
5. Papaioannou I., Betz W., Zwirglmaier K., Straub D. (2015). MCMC algorithms for subset simulation. *Probabilistic Engineering Mechanics*, 41, pp. 89–103.
6. Ullmann E., Papaioannou I. (2015). Multilevel estimation of rare events. *SIAM/ASA Journal on Uncertainty Quantification*, 3(1), pp. 922–953.

1.4 Multilevel Monte Carlo (C. Proppe)

1. Biehler J. (2016). Efficient uncertainty quantification for large-scale biomechanical models using a Bayesian multi-fidelity approach. PhD thesis. TU Munich, Germany.
2. Elfverson D., Hellman F., Målqvist A. (2016). A multilevel Monte Carlo method for computing failure probabilities. *SIAM/ASA Journal on Uncertainty Quantification*, 4(1), pp. 312–330.
3. Giles M.B. (2015). Multilevel Monte Carlo methods. *Acta Numerica*, 24, pp. 259–328.
4. Peherstorfer B., Willcox K., Gunzburger M. (2018). Survey of multifidelity methods in uncertainty propagation, inference, and optimization. *SIAM Review*, 60(3), pp. 550–591.
5. Ullmann E., Papaioannou I. (2015). Multilevel estimation of rare events. *SIAM/ASA Journal on Uncertainty Quantification*, 3(1), pp. 922–953.

2 Tuesday (September 3, 2019)

2.1 Introduction to random processes (F. Poirion)

1. Aubry N., Guyonnet R., Lima R. (1991). Spatiotemporal analysis of complex signals: Theory and applications. *Journal of Statistical Physics*, 64(3), pp. 683–739.
2. Besse P. (1991). Approximation spline de l'analyse en composantes principales d'une variable aléatoire hilbertienne. *Annales de la Faculté de Toulouse*, 12(3), pp. 329–349.
3. Cacoullos T. (1966). Estimation of a multivariate density. *Annals of the Institute of Statistical Mathematics*, 18, pp. 179–189.
4. Dauxois J., Pousse A., Romain Y. (1982). Asymptotic theory for the principal component analysis of a vector random function: Some applications to statistical inference. *Journal of Multivariate Analysis*. 1, pp. 136–154.
5. Devroye L., Györfi L. (1985). *Nonparametric density estimation: the L_1 view*. John Wiley, New York.
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7. Poirion F., Zentner I. (2012). Non-Gaussian non-stationary models for natural hazard modelling. *Applied Mathematical Modelling*, 37, pp. 5938–5950.
8. Poirion F., Zentner I. (2014). Stochastic model construction of observed random phenomena. *Probabilistic Engineering Mechanics*, 36, pp. 63–71.
9. Poirion F. (2016). Karhunen Loève expansion and distribution of non Gaussian process maximum. *Probabilistic Engineering Mechanics*, 43, pp. 85–90.
10. Scott D.W. (1992). *Multivariate density estimation: Theory, practice, and visualization*. John Wiley & Sons.
11. Silverman B.W. (1986). *Density estimation for statistics and data analysis*. Chapman & Hall.
12. Venturi D. (2011). A fully symmetric nonlinear biorthogonal decomposition theory for random fields. *Physica D: Nonlinear phenomena*, 240(4), pp. 415–425.
13. Zentner I., Ferré G., Poirion F., Benoit M. (2016). A biorthogonal decomposition for the identification and simulation of non-stationary and non-Gaussian random fields. *Journal of Computational Physics*, 314, pp. 1–13.
14. Zentner I., Poirion F. (2012). Enrichment of seismic ground motion data basis using Karhunen-Loève expansion. *Earthquake Engineering and Structural Dynamics*, 41(14), pp. 1945–1957.

2.2 Random processes: identification and simulation (F. Poirion)

See Section 2.1.

2.3 Polynomial chaos expansion (B. Sudret)

1. Blatman G. (2009). Adaptive sparse polynomial chaos expansions for uncertainty propagation and sensitivity analysis. PhD thesis. Université Blaise Pascal, Clermont Ferrand, France.
2. Le Gratiet L., Marelli S., Sudret B. (2016). Metamodel-based sensitivity analysis: Polynomial chaos expansions and Gaussian processes. In: *Handbook of Uncertainty Quantification*. Ed. by R. Ghanem, D. Higdon, H. Owhadi. Springer International Publishing, pp. 1–37.
3. Sudret B. (2008). Global sensitivity analysis using polynomial chaos expansions. *Reliability Engineering & System Safety*, 93(7), pp. 964–979.
4. Sudret B. (2014). Polynomial chaos expansions and stochastic finite element methods. In: *Risk and Reliability in Geotechnical Engineering*. Ed. by K.-K. Phoon, J. Ching. CRC Press. Chap. 6, pp. 265–300.

2.4 Sparse polynomial chaos expansion (B. Sudret)

1. Blatman G., Sudret B. (2011). Adaptive sparse polynomial chaos expansion based on least angle regression. *Journal of Computational Physics*, 230(6), pp. 2345–2367.
2. Mai C., Sudret B. (2017). Surrogate models for oscillatory systems using sparse polynomial chaos expansions and stochastic time warping. *SIAM/ASA Journal on Uncertainty Quantification*, 5(1), pp. 540–571.
3. Mai C.V. (2016). Polynomial chaos expansions for uncertain dynamical systems - Applications in earthquake engineering. PhD thesis. ETH Zurich, Switzerland.
4. Mai C.V., Spiridonakos M.D., Chatzi E.N., Sudret B. (2016). Surrogate modeling for stochastic dynamical systems by combining nonlinear autoregressive with exogenous input models and polynomial chaos expansions. *International Journal for Uncertainty Quantification*, 6(4), pp. 313–339.
5. Yaghoubi V., Marelli S., Sudret B., Abrahamsson T. (2017). Sparse polynomial chaos expansions of frequency response functions using stochastic frequency transformation. *Probabilistic Engineering Mechanics*, 48, pp. 39–58.

3 Wednesday (September 4, 2019)

3.1 Low-rank approximation (M. Chevreuil)

1. Chevreuil M., Lebrun R., Nouy A., Rai P. (2015). A least-squares method for sparse low rank approximation of multivariate functions. *SIAM/ASA Journal on Uncertainty Quantification*, 3(1), pp. 897–921.
2. Hackbusch W. (2012). *Tensor spaces and numerical tensor calculus*. Vol. 42. Springer Series in Computational Mathematics. Heidelberg: Springer.
3. Nouy A. (2016). Low-rank tensor methods for model order reduction. In: *Handbook of Uncertainty Quantification*. Ed. by R. Ghanem, D. Higdon, H. Owhadi. Cham: Springer International Publishing, pp. 1–26.
4. Rai P. (2009). Sparse low rank approximation of multivariate functions - Applications in uncertainty quantification. PhD thesis. Ecole Centrale Nantes, Nantes, France.

3.2 Support vector machines (J.-M. Bourinet)

1. Bourinet J.-M. (2018b). Reliability analysis and optimal design under uncertainty – Focus on adaptive surrogate-based approaches. HDR Report. Université Clermont Auvergne, France. See Chapter II: Surrogate models & adaptive strategies for uncertainty propagation.
2. Chapelle O. (2004). Support vector machines: principes d'induction, réglage automatique et connaissances a priori. PhD thesis (in English). Université Pierre et Marie Curie - Paris VI, Paris, France.
3. Smola A.J., Schölkopf B. (1998). *A tutorial on support vector regression*. NeuroCOLT Technical Report NC-TR-98-030. Royal Holloway College, University of London, UK.
4. Smola A.J., Bartlett P., Schölkopf B., Schuurmans D., eds. (2000). *Advances in large margin classifiers*. Cambridge, MA, USA: MIT Press.
5. Vapnik V. (1995). *The nature of statistical learning theory*. New York, NY, USA: Springer-Verlag.

3.3 Kriging (R. Le Riche)

1. Durrande N., Le Riche R. (2017). *Introduction to Gaussian process surrogate models*. MDIS Fall School, Clermont Ferrand, October 16, 2017.
2. Le Riche R., Mohammadi H., Durrande N., Touboul E., Bay X. (2017). A comparison of regularization methods for Gaussian processes. SIAM Conference on Optimization, Vancouver, Canada, May 22-25, 2017.
3. Mohammadi H., Le Riche R., Durrande N., Touboul E., Bay X. (2017). *An analytic comparison of regularization methods for Gaussian processes*. Research Report. Ecole Nationale Supérieure des Mines de Saint-Etienne ; LIMOS.
4. O'Hagan A. (2006). Bayesian analysis of computer code outputs: A tutorial. *Reliability Engineering & System Safety*, 91(10), pp. 1290–1300.
5. Rasmussen C.E., Williams C.K.I. (2006). *Gaussian processes for machine learning*. 2nd ed. Cambridge, MA, USA: MIT Press.
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3.4 Global sensitivity analysis (B. Iooss)

1. Baudin M., Dutfoy A., Iooss B., Popelin A.-L. (2017). OpenTURNS: An industrial software for uncertainty quantification in simulation. In: *Handbook of Uncertainty Quantification*. Ed. by R. Ghanem, D. Higdon, H. Owhadi. Cham: Springer International Publishing, pp. 2001–2038.
2. Iooss B. (2018). Sensitivity analysis of model outputs: Principles, methods and issues for BEPU methodology. In: *Proc. ANS Best Estimate Plus Uncertainty International Conference (BEPU 2018), Real Collegio, Lucca, Italy, May 13–19, 2018*.
3. Iooss B., Lemaître P. (2015). A Review on global sensitivity analysis methods. In: *Uncertainty Management in Simulation-Optimization of Complex Systems: Algorithms and Applications*. Ed. by G. Dellino, C. Meloni. Boston, MA: Springer US, pp. 101–122.
4. Le Gratiet L., Marelli S., Sudret B. (2017). Metamodel-based sensitivity analysis: Polynomial chaos expansions and Gaussian processes. In: *Handbook of Uncertainty Quantification*. Ed. by R. Ghanem, D. Higdon, H. Owhadi. Cham: Springer International Publishing, pp. 1289–1325.
5. Perrin G., Defaux G. (2019). Efficient evaluation of reliability-oriented sensitivity indices. *Journal of Scientific Computing*.
6. Storlie C.B., Helton J.C. (2008). Multiple predictor smoothing methods for sensitivity analysis: Description of techniques. *Reliability Engineering & System Safety*, 93(1), pp. 28–54.
7. Woods D.C., Lewis S.M. (2016). Design of experiments for screening. In: *Handbook of Uncertainty Quantification*. Ed. by R. Ghanem, D. Higdon, H. Owhadi. Cham: Springer International Publishing, pp. 1–43.

4 Thursday (September 5, 2019)

4.1 Optimization under uncertainty (R. Le Riche)

1. Balesdent M., Brevault L., Morio J., Chocat R. (2019). In: *Traitements des incertitudes en ingénierie mécanique*. Ed. by C. Gogu. Traité Sciences. In preparation. ISTE. Chap. 5: Overview of problem formulations and optimization algorithms in the presence of uncertainty.
2. Ben-Tal A., El Ghaoui L., Nemirovski A. (2009). *Robust optimization*. Princeton University Press.
3. Beyer H.-G., Sendhoff B. (2007). Robust optimization - a comprehensive survey. *Computer Methods in Applied Mechanics and Engineering*, 196(33), pp. 3190–3218.
4. Breitkopf P., Filomeno Coelho R. (2013). *Multidisciplinary design optimization in computational mechanics*. Wiley.
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6. Lemaire M., Chateauneuf A., Mitteau J.-C. (2010). *Structural reliability*. ISTE.
7. Melchers R.E. (1999). *Structural reliability analysis and prediction*. 2nd ed. Wiley.
8. Spall J.C. (2003). *Introduction to stochastic search and optimization: estimation, simulation, and control*. Wiley.
9. Valdebenito M.A., Schuëller G.I. (2010). A survey on approaches for reliability-based optimization. *Structural and Multidisciplinary Optimization*, 42(5), pp. 645–663.

4.2 Structural health monitoring (J. Goulet)

1. Goulet J.-A. (2020). Chapter 12 - State-space models. In: *Probabilistic machine learning for civil engineers*. In preparation.

5 Friday (September 6, 2019)

5.1 Inverse methods (B. Rosić)

1. Dashti M., Stuart A.M. (2013). The Bayesian approach to inverse problems. *arXiv e-prints*.
2. Evensen G. (2003). The ensemble Kalman filter: theoretical formulation and practical implementation. *Ocean Dynamics*, 53(4), pp. 343–367.
3. Matthies H.G., Zander E., Rosić B.V., Litvinenko A., Pajonk O. (2016). Inverse problems in a Bayesian setting. In: *Computational Methods for Solids and Fluids: Multiscale Analysis, Probability Aspects and Model Reduction*. Ed. by A. Ibrahimbegovic. Springer, pp. 245–286.
4. Tarantola A. (2005). *Inverse problem theory and methods for model parameter estimation*. SIAM.

5.2 Bayesian updating (I. Papaioannou)

1. Betz W., Papaioannou I., Beck J.L., Straub D. (2018). Bayesian inference with subset simulation: Strategies and improvements. *Computer Methods in Applied Mechanics and Engineering*, 331, pp. 72–93.
2. Chopin N. (2002). A sequential particle filter method for static models. *Biometrika*, 89(3), pp. 539–551.
3. Del Moral P., Doucet A., Jasra A. (2006). Sequential Monte Carlo samplers. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, 68(3), pp. 411–436.
4. Roberts G.O., Rosenthal J.S. (2001). Optimal scaling for various Metropolis-Hastings algorithms. *Statistical Science*, 16(4), pp. 351–367.
5. Straub D., Papaioannou I. (2014). Risk and Reliability in Geotechnical Engineering. In: ed. by K.-K. Phoon, J. Ching. CRC Press. Chap. 5: Bayesian analysis for learning and updating geotechnical parameters and models with measurements, pp. 221–264.
6. Straub D., Papaioannou I. (2015). Bayesian updating with structural reliability methods. *Journal of Engineering Mechanics*, 141(3), p. 04014134.
7. Straub D., Papaioannou I., Betz W. (2016). Bayesian analysis of rare events. *Journal of Computational Physics*, 314, pp. 538–556.