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AI Research Science Manager
Facebook Reality Labs

Kevin Carlberg

My research combines concepts from machine learning, computational physics, and high-performance computing to drastically reduce the cost of simulating nonlinear dynamical systems at extreme scale.

Research interests

Model reduction • Machine learning • Computational physics • Deep learning • Dimensionality reduction • Numerical optimization • Uncertainty quantification • High-performance computing

Positions

Apr 2020– **AI Research Science Manager**, *Facebook Reality Labs*, Redmond, WA.

Sept 2019–Apr 2020 **Machine Learning Research Scientist**, *Facebook Reality Labs*, Redmond, WA.

Oct 2019– **Affiliate Associate Professor of Applied Mathematics and Mechanical Engineering**, *University of Washington*, Seattle, WA.

May 2019–Aug 2019 **Distinguished Member of Technical Staff**, *Sandia National Laboratories*, Livermore, CA.

Oct 2014–Apr 2019 **Principal Member of Technical Staff**, *Sandia National Laboratories*, Livermore, CA.

Oct 2011–Sept 2014 **President Harry S. Truman Fellow**, *Sandia National Laboratories*, Livermore, CA.

Education

2006–2011 **Stanford University**, *PhD, Aeronautics & Astronautics.*
PhD Minor: Computational and Mathematical Engineering
Adviser: Charbel Farhat
GPA: 4.15/4.0

2005–2006 **Stanford University**, *MS, Aeronautics & Astronautics.*
GPA: 4.21/4.0, Ranked 1st in Aeronautics & Astronautics

2001–2005 **Washington University in St. Louis**, *BS, Mechanical Engineering.*
GPA: 4.0/4.0, summa cum laude, Ranked 1st in School of Engineering & Applied Science

Highlights

- 9 research grants funded as Principal Investigator (PI) for over $10M total.
- Have directly supervised 11 postdocs, 18 PhD candidates, 2 MS candidates, and 6 BS candidates.
- 36 publications, including
  - *#1 most cited paper, 2020*, Journal of Computational Physics: [9]
  - *#1 most cited paper, 2013*, Journal of Computational Physics: [26]
  - *#2 most cited paper, 2011*, International Journal for Numerical Methods in Engineering: [28]
  - *Featured article, June 2015*, SIAM Journal on Scientific Computing: [24]
- 3 research fellowships, including the Truman Fellowship at Sandia National Laboratories.
- Model-reduction methods implemented in 4 massively parallel computational-physics codes.
- Ranked first in:
  - Stanford University Aeronautics & Astronautics MS Class of 2006.
  - Washington University School of Engineering & Applied Science BS Class of 2005.
- 2 keynote lectures, 7 plenary lectures, 35 invited talks, 34 conference talks.
- Associate Editor for SIAM Journal on Scientific Computing.

Funding and proposals

June 2019– Sept 2019 **Combining deep learning and model reduction via deep convolutional autoencoders (PI)**, *$75K total: $75K (2019)*, Funding source: National Nuclear Security Administration, Advanced Simulation and Computing (ASC), Advanced Machine Learning.

Oct 2018– Sept 2021 **Revolutionizing weapons-component design via advanced uncertainty quantification and reduced-order modeling (PI)**, *$1.56M total: $502K (2019), $520K (2020), $541K (2021)*, Funding source: Sandia National Laboratories' Laboratory-Directed Research & Development.

Oct 2018– Sept 2021 **Rapid high-fidelity aerothermal responses with quantified uncertainties via reduced-order modeling (PI)**, *$1.38M total: $446K (2019), $456K (2020), $474K (2021)*, Funding source: Sandia National Laboratories' Laboratory-Directed Research & Development.

Oct 2018– **Agile 'Lego-like' full-system design with domain-decomposition uncertainty quantification and reduced-order modeling (PI)**, *$150K total: $150K (2019)*, Funding source: Sandia National Laboratories' Laboratory-Directed Research & Development.

June 2016– **Bayesian inference for seismic wave propagation (PI)**, *$250K total: $100K (2016), $150K (2017)*, Funding source: National Nuclear Security Administration, Nonproliferation Research and Development (NA-22).

Oct 2015– Sept 2018 **Subsystem ROM and UQ for rapid, agile, extreme-scale simulation (PI)**, *$1.59M total: $494K (2016), $510K (2017), $581K (2018)*, Funding source: Sandia National Laboratories' Laboratory-Directed Research & Development.

Oct 2014– **Rigorous surrogates for quantifying margins of uncertainty (PI)** , *$1.98M total: $230K (2015), $275K (2016), $350K (2017), $375K (2018), $750K (2019)*, Funding source: National Nuclear Security Administration, Advanced Simulation and Computing (ASC), Verification & Validation Methods.

Oct 2014– **Advanced ROM methods for thermomechanical responses (PI)**, *$1.96M total: $400K (2015), $425K (2016), $338K (2017), $400K (2018), $400K (2019)*, Funding source: National Nuclear Security Administration, Advanced Simulation and Computing (ASC), Verification & Validation Methods.

Oct 2011– Sept 2014 **Real-time analysis and optimization of high-fidelity nonlinear models via model reduction (PI)**, *$810K total: $260K (2012), $290K (2013), $260K (2014)*, Funding source: Sandia National Laboratories' Laboratory-Directed Research & Development.

Honors and awards

2011–2014 **Truman Fellowship**, Sandia National Laboratories.

2008–2010 **National Science Foundation Graduate Research Fellowship**, Stanford University.

2008 **CEA-EDF-INRIA Numerical Analysis Summer School Scholarship**, Paris, France.

2007 **Nicholas J. Hoff Award**, *ranked 1st in graduating MS class of Aeronautics & Astronautics*, Stanford University.

2006 **Ranked 1st of 16 in Aeronautics & Astronautics PhD qualifying exams**, Stanford University.

2005–2008 **National Defense Science and Engineering Graduate Fellowship**, Stanford University.

2005 **Gustav Mesmer Prize**, *ranked 1st in graduating BS class of Mechanical Engineering*, Washington University in St. Louis.

2001–2005 **Calvin L. Woodward Fellowship**, Washington University in St. Louis.

2001–2005 **Danforth Scholarship**, Washington University in St. Louis.

Journal publications

Preprints

[1] F. Rizzi, P. Blonigan, and K. Carlberg. Pressio: Enabling projection-based model reduction for large-scale nonlinear dynamical systems. *arXiv e-print*, (2003.07798), 2020.

[2] E. Parish and K. Carlberg. Windowed least-squares model reduction for dynamical systems. *arXiv e-print*, (1910.11388), 2019.

[3] K. Lee and K. Carlberg. Deep conservation: A latent dynamics model for exact satisfaction of physical conservation laws. *arXiv e-print*, (1909.09754), 2019.

[4] K. Carlberg, S. Guzzetti, M. Khalil, and K. Sargsyan. The network uncertainty quantification method for propagating uncertainties in component-based systems. *arXiv e-print*, (1908.11476), 2019.

[5] S. Pagani, A. Manzoni, and K. Carlberg. Statistical closure modeling for reduced-order models of stationary systems by the ROMES method. *arXiv e-print*, (1901.02792), 2019.

[6] L. Peng and K. Carlberg. Structure-preserving model reduction for marginally stable LTI systems. *arXiv e-print*, (1703.04009), 2017.

Published

[7] P. Etter and K. Carlberg. Online adaptive basis refinement and compression for reduced-order models via vector-space sieving. *Computer Methods in Applied Mechanics and Engineering*, 364:112931, 2020.

[8] E. Parish and K. Carlberg. Time-series machine-learning error models for approximate solutions to parameterized dynamical systems. *Computer Methods in Applied Mechanics and Engineering*, 365:112990, 2020.

[9] K. Lee and K. Carlberg. Model reduction of dynamical systems on nonlinear manifolds using deep convolutional autoencoders. *Journal of Computational Physics*, 404:108973, 2020.
#1 most cited paper of 2020, Journal of Computational Physics.

[10] S. Guzzetti, L. Mansilla Alvarez, P. J. Blanco, K. Carlberg, and A. Veneziani. Propagating uncertainties in large-scale hemodynamics models via network uncertainty quantification and reduced-order modeling. *Computer Methods in Applied Mechanics and Engineering*, 358:112626, 2020.

[11] K. Carlberg, A. Jameson, M. Kochenderfer, J. Morton, L. Peng, and F. Witherden. Recovering missing CFD data for high-order discretizations using deep neural networks and dynamics learning. *Journal of Computational Physics*, 395:105–124, 2019.

[12] M. Zahr, K. Carlberg, and D. Kouri. An efficient, globally convergent method for optimization under uncertainty using adaptive model reduction and sparse grids. *SIAM/ASA Journal on Uncertainty Quantification*, 6(3):877–912, 2019.

[13] K. Carlberg, L. Brencher, B. Haasdonk, and A. Barth. Data-driven time parallelism via forecasting. *SIAM Journal on Scientific Computing*, 41(3):B466–B496, 2019.

[14] B. Freno and K. Carlberg. Machine-learning error models for approximate solutions to parameterized systems of nonlinear equations. *Computer Methods in Applied Mechanics and Engineering*, 348:250–296, 2019.

[15] Y. Choi and K. Carlberg. Space–time least-squares Petrov–Galerkin projection for nonlinear model reduction. *SIAM Journal on Scientific Computing*, 41(1):A26–A58, 2019.

[16] K. Carlberg, Y. Choi, and S. Sargsyan. Conservative model reduction for finite-volume models. *Journal of Computational Physics*, 371:280–314, 2018.

[17] K. Lee, K. Carlberg, and H. Elman. Stochastic least-squares Petrov–Galerkin method for parameterized linear systems. *SIAM/ASA Journal on Uncertainty Quantification*, 6(1):374–396, 2018.

[18] J. Tencer, K. Carlberg, M. Larsen, and R. Hogan. Accelerated solution of discrete ordinates approximation to the Boltzmann transport equation via model reduction. *Journal of Heat Transfer*, 139(12):122701, 2017.

[19] S. Trehan, K. Carlberg, and L. Durlofsky. Error modeling for surrogates of dynamical systems using machine learning. *International Journal for Numerical Methods in Engineering*, 112(12):1801–1827, 2017.

[20] K. Carlberg, M. Barone, and H. Antil. Galerkin v. least-squares Petrov–Galerkin projection in nonlinear model reduction. *Journal of Computational Physics*, 330:693–734, 2017.

[21] K. Carlberg, V. Forstall, and R. Tuminaro. Krylov-subspace recycling via the POD-augmented conjugate-gradient method. *SIAM Journal on Matrix Analysis and Applications*, 37(3):1304–1336, 2016.

[22] K. Carlberg, J. Ray, and B. van Bloemen Waanders. Decreasing the temporal complexity for nonlinear, implicit reduced-order models by forecasting. *Computer Methods in Applied Mechanics and Engineering*, 289:79–103, 2015.

[23] M. Drohmann and K. Carlberg. The ROMES method for statistical modeling of reduced-order-model error. *SIAM/ASA Journal on Uncertainty Quantification*, 3(1):116–145, 2015.

[24] K. Carlberg, R. Tuminaro, and P. Boggs. Preserving Lagrangian structure in nonlinear model reduction with application to structural dynamics. *SIAM Journal on Scientific Computing*, 37(2):B153–B184, 2015.
Featured article, June 2015, SIAM Journal on Scientific Computing.

[25] K. Carlberg. Adaptive h-refinement for reduced-order models. *International Journal for Numerical Methods in Engineering*, 102(5):1192–1210, 2015.

[26] K. Carlberg, C. Farhat, J. Cortial, and D. Amsallem. The GNAT method for nonlinear model reduction: effective implementation and application to computational fluid dynamics and turbulent flows. *Journal of Computational Physics*, 242:623–647, 2013. **#1 most cited paper of 2013, Journal of Computational Physics**.

[27] K. Carlberg and C. Farhat. A low-cost, goal-oriented 'compact proper orthogonal decomposition' basis for model reduction of static systems. *International Journal for Numerical Methods in Engineering*, 86(3):381–402, April 2011.

[28] K. Carlberg, C. Farhat, and C. Bou-Mosleh. Efficient non-linear model reduction via a least-squares Petrov–Galerkin projection and compressive tensor approximations. *International Journal for Numerical Methods in Engineering*, 86(2):155–181, April 2011. **#2 most cited paper of 2011, International Journal for Numerical Methods in Engineering**.

[29] D. Amsallem, J. Cortial, K. Carlberg, and C. Farhat. A method for interpolating on manifolds structural dynamics reduced-order models. *International Journal for Numerical Methods in Engineering*, 80(9):1241–1258, 2009.

Conference proceedings (refereed)

[30] P. Blonigan, K. Carlberg, F. Rizzi, M. Howard, and J. Fike. Model reduction for hypersonic aerodynamics via conservative lspg projection and hyper-reduction. *AIAA Paper 2020-0104, AIAA Scitech 2020 Forum, Orlando, FL*, January 6–10, 2020.

[31] J. Tencer, K. Carlberg, R. Hogan, and M. Larsen. Reduced order modeling applied to the discrete ordinates method for radiation heat transfer in participating media. *HT 2016-7010, ASME 2016 Summer Heat Transfer Conference, Washington, DC*, July 10–14, 2016.

[32] K. Carlberg, R. Tuminaro, and P. Boggs. Efficient structure-preserving model reduction for nonlinear mechanical systems with application to structural dynamics. *AIAA Paper 2012-1969, 53rd AIAA/ASME/ASCE/AHS/ASC Structures, Structural Dynamics and Materials Conference, Honolulu, HI*, April 23–26, 2012.

[33] K. Carlberg, J. Cortial, D. Amsallem, M. Zahr, and C. Farhat. The GNAT nonlinear model reduction method and its application to fluid dynamics problems. *AIAA Paper 2011-3112, 6th AIAA Theoretical Fluid Mechanics Conference, Honolulu, HI*, June 27–30, 2011.

[34] R. Stephan and K. Carlberg. Gappy data reconstruction and applications in archaeology. In *Proceedings of the XXXVIII Annual Conference on Computer Applications and Quantitative Methods in Archaeology, Granada, Spain*, April 6–9, 2010.

[35] K. Carlberg and C. Farhat. An adaptive POD-Krylov reduced-order model for structural optimization. *8th World Congress on Structural and Multidisciplinary Optimization, Lisbon, Portugal*, June 1–5, 2009.

[36] K. Carlberg and C. Farhat. A compact proper orthogonal decomposition basis for optimization-oriented reduced-order models. *AIAA Paper 2008-5964, 12th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, Victoria, Canada*, September 10–12, 2008.

Research codes

My nonlinear model-reduction techniques are implemented in the following massively parallel computational-mechanics codes:

- **Pressio**, *Non-intrusive "wrapper" code*, Sandia National Laboratories, *Model-reduction implementation*: F. Rizzi (lead), P. Blonigan, C. Hoang, K. Carlberg.
- **SPARC**, *Computational fluid dynamics*, Sandia National Laboratories, *Model-reduction implementation*: J. Fike (lead), K. Carlberg, M. Barone, I. Tezaur.
- **Albany**, *Multiphysics finite-element analysis*, Sandia National Laboratories, *Model-reduction implementation*: J. Cortial (lead), K. Carlberg.
  github.com/gahansen/Albany
- **AERO-F**, *Computational fluid dynamics*, Stanford University, *Model-reduction implementation*: K. Carlberg (lead), J. Cortial, C. Bou-Mosleh, D. Amsallem.
  bitbucket.org/frg/aero-f

Research advising

Postdoctoral researchers

Mar 2019–Sept 2019 **Yukiko Shimizu**, *Postdoctoral Researcher*, Sandia National Laboratories.
Project: Deep learning for multidimensional nonlinear model reduction

Aug 2018–Sept 2019 **Eric Parish**, *John von Neumann Postdoctoral Fellow*, Sandia National Laboratories.
Project: Error modeling for nonlinear dynamical systems

Aug 2018–Sept 2019 **Kookjin Lee**, *Postdoctoral researcher*, Sandia National Laboratories.
Project: Deep learning for nonlinear model reduction

Sept 2017–Apr 2018 **Payton Lindsey**, *Postdoctoral researcher*, Sandia National Laboratories.
Project: Model reduction and machine learning for finite-element multiphysics simulations

Aug 2017–Sept 2019 **Thomas Catanach**, *John von Neumann Postdoctoral Fellow*, Sandia National Laboratories.
Project: Dynamical-system-informed posterior samplers for Bayesian inference

May 2016–Apr 2018 **Liqian Peng**, *Postdoctoral researcher*, Sandia National Laboratories.
Project: Model reduction for large-scale linear dynamical systems

Feb 2016–Mar 2019 **Chi Hoang**, *Postdoctoral researcher*, Sandia National Laboratories.
Project: Subsystem model reduction

Dec 2015–Mar 2017 **Youngsoo Choi**, *Postdoctoral researcher*, Sandia National Laboratories.
Project: Space–time least-squares Petrov–Galerkin nonlinear model reduction

Sept 2014–Sept 2016 **Jeffrey Fike**, *Postdoctoral researcher*, Sandia National Laboratories.
Project: Model reduction for thermomechanical responses

Oct 2012–Sept 2014 **Martin Drohmann**, *Postdoctoral researcher*, Sandia National Laboratories.
Project: Uncertainty quantification for reduced-order models

Feb 2012–Nov 2013 **Julien Cortial**, *Postdoctoral researcher*, Sandia National Laboratories.
Project: A Trilinos-based module for nonlinear model reduction

PhD candidates

July 2019–Sept 2019 **Alexander Schein**, *Technical University of Munich*.
Project: Optimization-based model reduction on nonlinear manifolds

June 2019– Sept 2019 **Nirmal Nair**, *University of Illinois, Urbana–Champaign*.
Project: Guaranteeing generalizability for manifold reduced-order models with transfer learning

June 2019– Sept 2019 **Samuel Majors**, *University of Texas at Austin*.
Project: Comparing deep convolutional autoencoders with linear subspaces in model reduction

June 2018– Mar 2019 **Philip Etter**, *Stanford University*.
Project: Online adaptive basis refinement and compression for reduced-order models

June 2018– Aug 2018 **Ricardo Baptista**, *Massachusetts Institute of Technology*.
Project: Machine learning for uncertainty quantification

June–Sept 2017 **Danielle Maddix**, *Stanford University*.
Project: Structure-preserving nonlinear model reduction for compressible fluid dynamics

Feb–Sept 2017 **Dennis Grunert**, *University of Stuttgart*.
Project: Non-intrusive least-squares Petrov–Galerkin projection in nonlinear model reduction

June 2016– **Zhe Bai**, *University of Washington*.
Project: Non-intrusive Galerkin projection in nonlinear model reduction

June–Sept 2016 **Jiahua Jiang**, *University of Massachusetts, Dartmouth*.
Project: Anderson acceleration for domain decomposition methods in uncertainty quantification

June–Sept 2016 **Hasan Cagan Ozen**, *Columbia University*.
Project: Bayesian inference in large-scale networks

May 2016– Jan 2017 **Kookjin Lee**, *University of Maryland*.
Project: Optimal intrusive uncertainty quantification

May 2016– **Sofia Guzzetti**, *Emory University*.
Project: Multigrid for accelerating domain decomposition methods in uncertainty quantification

May 2016– **Wayne Uy**, *Cornell University*.
Project: Bayesian inference with reduced-order-model error surrogates

June 2015– June 2016 **Syuzanna Sargsyan**, *University of Washington*.
Project: Reduced-order models for nonlinear compressible fluid dynamics

May–Aug 2015 **Katarzyna Swirydowicz**, *Virginia Tech*.
Project: Generalized Krylov-subspace methods for extreme-scale architectures

Mar 2015– Sept 2016 **Matthew Zahr**, *Stanford University*.
Project: Optimization under uncertainty with reduced-order models

Feb 2015– Jan 2017 **Sumeet Trehan**, *Stanford University*.
Project: Automated construction error surrogates via statistical learning

May 2014– Sept 2015 **Virginia Forstall**, *University of Maryland*.
Project: Applying model reduction to Krylov-subspace iterative methods via recycling

MS candidates

Fall 2010 **Wade Spurlock**, *Stanford University*.
Project: Visualizing nonlinear model reduction methods for Formula One car design

Fall 2009 **Paul Covington**, *Stanford University*.
Project: Implementing shape sensitivity analysis in a massively parallel fluid code

BS candidates

Sept–Dec 2018 **Anran Lu**, *Stanford University*.
Project: Optimization and reduced-order modeling

Sept–Dec 2018 **Yiwen Guo**, *Stanford University*.
Project: Optimization and reduced-order modeling

Apr–Dec 2018 **Remmelt Ammerlaan**, *Stanford University*.
Project: A Python library for advanced nonlinear reduced-order modeling

Apr–June 2018 **Kexin Yu**, *Stanford University*.
Project: A Python library for advanced nonlinear reduced-order modeling

Apr–Oct 2015 **Lukas Brencher**, *University of Stuttgart*, Germany.
Project: Enabling data-driven time parallelism for reduced-order models

Summer 2010 **Matthew Zahr**, *University of California, Berkeley*.
Project: Comparing model reduction methods on linear and nonlinear electrical, mechanical, and biological systems. Won "best project" at AHPCRC 2010 Summer Institute.

Teaching

Summer 2017, 2018, 2019, 2020 **Instructor and Curriculum Co-Developer**, *Introduction to Mathematical Optimization (short course)*, Institute for Computational and Mathematical Engineering (ICME) Fundamentals of Data Science Summer Workshops, Stanford, CA.

Summer 2009, 2010 **Instructor and Curriculum Developer**, *Introduction to Engineering Optimization (short course)*, Army High-Performance Computing Research Center Summer Institute, Stanford, CA.

Spring 2010 **Teaching Assistant**, *Large-Scale Numerical Optimization (CME 338)*, Stanford University, Prof Michael Saunders.

Fall 2004, Spring 2005 **Teaching Assistant**, *Mechanics of Deformable Bodies (ME 241)*, Washington University in St. Louis, Prof Barna Szabó.

Service

2019– **Editorial board**.
- *SIAM Journal on Scientific Computing.* January 2019–, *Associate Editor.*

2021– **Professional committee member**.
- *SIAM Industry Committee.* January 2021–, *Committee Member.*

2018– **Ph.D. thesis committee member**.
- *Babak Maboudi Afkham*, École Polytechnique Fédérale de Lausanne (EPFL), 2018. *Adviser*: Prof. Jan Hesthaven.

2015– **Conference committee member**.
- SIAM Conference on Computational Science and Engineering, Winter 2021, *organizing committee.*
- ICERM Workshop on Algorithms for dimension and complexity reduction, March 16–20, 2020, Providence, Rhode Island, *organizing committee.*
- Model Reduction of Parametrized Systems (MoRePaS) IV, Nantes, France, April 10–13, 2018, *scientific committee.*
- SIAM Annual Meeting, Boston, MA, July 11–15, 2016, *organizing committee.*
- International Conference on Advances in Computational Tools for Engineering Applications, Louaize, Lebanon, July 11–13, 2016, *technical program committee.*

2014– **Workshop organizer**.

- Bay Area Scientific Computing Day, Sandia National Laboratories, Livermore, CA, Dec 7, 2018. *Organizers*: K. Carlberg, K. Sargsyan.
- West Coast ROM Workshop, Lawrence Berkeley National Laboratories, Berkeley, CA, Nov 17, 2017. *Organizers*: K. Carlberg, M. Zahr.
- West Coast ROM Workshop, Sandia National Laboratories, Livermore, CA, Nov 19, 2015. *Organizers*: K. Carlberg, D. Amsallem.
- Bay Area ROM Workshop, Sandia National Laboratories, Livermore, CA, Aug 7, 2014. *Organizer*: K. Carlberg.

2012– **Minisymposium organizer**.

- K. Carlberg and B. Kramer, "Data-augmented reduced-order modeling: operator learning and closure/error modeling," 2019 SIAM Conf on Comp Sci & Eng, Spokane, Washington, February 25–March 1, 2019.
- K. Carlberg and A. Manzoni, "Reduced-order Modeling Techniques for Large-scale UQ Problems," 2018 SIAM Conf on Uncertainty Quantification, Garden Grove, California, April 16–19, 2018.
- K. Carlberg and M. Yano, "Model reduction in computational fluid dynamics," 14th U.S. National Congress on Computational Mechanics, Montréal, Canada, July 17–20, 2017.
- K. Carlberg, F. Lu, and M. Morzfeld, "Numerical methods for uncertainty quantification, surrogate models, and Bayesian inference," 2017 SIAM Conf on Comp Sci & Eng, Atlanta, GA, February 27–March 3, 2017.
- K. Carlberg and K. Duraisamy, "Data and Dynamical-System Models," 2016 SIAM Annual Meeting, Boston, MA, July 11–15, 2016.
- K. Carlberg and A. Manzoni, "Reduced-Order Modeling in Uncertainty Quantification," 2016 SIAM Conf on Uncertainty Quantification, Lausanne, Switzerland, April 5–8, 2016.
- K. Carlberg and G. Rozza, "Recent Advances in Model Reduction," 2015 SIAM Conf on Comp Sci & Eng, Salt Lake City, UT, March 14–18, 2015.
- K. Carlberg and D. Kouri, "Model-Reduction Techniques for Quantifying and Controlling Uncertainty," 2014 SIAM Conf on Uncertainty Quantification, Savannah, GA, March 31–April 3, 2014.
- K. Carlberg and M. Drohmann, "Error analysis in model reduction," 2013 SIAM Conf on Comp Sci & Eng, Boston, MA, February 25–March 1, 2013.
- K. Carlberg, D. Amsallem, and C. Farhat, "Model Order Reductions," 10th World Congress on Computational Mechanics, São Paulo, Brazil, July 8–13, 2012.
- K. Carlberg and P. Constantine, "Model reduction for nonlinear dynamical systems," 2012 SIAM Conf on Uncertainty Quantification, Raleigh, NC, April 2–5, 2012.

2009– **Journal referee**.

- *Advances in Computational Mathematics*
- *Computational Mechanics*
- *Computer Methods in Applied Mechanics and Engineering*
- *Computers and Fluids*
- *ESAIM: Mathematical Modelling and Numerical Analysis*
- *International Journal for Numerical Methods in Engineering*
- *International Journal for Numerical Methods in Fluids*
- *International Journal for Uncertainty Quantification*
- *Journal of Computational and Applied Mechanics*
- *Journal of Computational Physics*
- *Journal of Scientific Computing*
- *Nonlinear Dynamics*
- *SIAM Journal on Matrix Analysis and Applications*
- *SIAM Journal on Optimization*
- *SIAM Journal on Scientific Computing*

2015– **Proposal reviewer**.
- *Air Force Office of Scientific Research*
- *Department of Energy Office of Science*
- *Natural Sciences and Engineering Research Council of Canada*
- *Society for Industrial and Applied Mathematics Books*

2016–2019 **John von Neumann Fellowship committee member**, *Sandia National Laboratories*, Livermore, CA.

2012–2019 **Recruiter**, *Sandia National Laboratories*, Livermore, CA.

2011 **External examiner for postgraduate courses**, *University of Pretoria*, South Africa.

Talks (* indicates travel support)

Keynote

1. * "Enabling UQ with expensive models: nonlinear model reduction and error surrogates," U2 can UQ showcase, University of Arizona, April 28, 2017.
2. * "Nonlinear model reduction: discrete optimality, h-adaptivity, and error surrogates," Data-Driven Model Order Reduction and Machine Learning, University of Stuttgart, Stuttgart, Germany, March 30–April 1, 2016.

Plenary

1. "Nonlinear model reduction: using machine learning to enable rapid simulation of extreme-scale physics models" AAAI 2020 Spring Symposium on Combining Artificial Intelligence and Machine Learning with Physics Sciences, Stanford University, Stanford, California, March 25, 2020.
2. * "Convolutional autoencoders and LSTMs: Using deep learning to overcome Kolmogorov-width limitations and accurately model errors in nonlinear model reduction" ICERM Workshop on Mathematics of Model Reduction, Brown University, Providence, Rhode Island, February 21, 2020.
3. * "Nonlinear model reduction: Using machine learning to enable rapid simulation of extreme-scale physics models ," Distinguished Speaker, NSF Workshop: Exuberance of Machine Learning in Transport Phenomena, Dallas, Texas, February 11, 2020.
4. * "Nonlinear reduced-order modeling: Using machine learning to enable rapid simulation of extreme-scale physics models," AI for Engineering, Toronto, Canada, August 21, 2019.
5. * "Nonlinear reduced-order modeling: Using machine learning to enable extreme-scale simulation for many-query problems," ICERM Workshop on Scientific Machine Learning, Brown University, Providence, Rhode Island, January 29, 2019.
6. * "Advances in nonlinear model reduction: least-squares Petrov–Galerkin projection and machine-learning error models," SAMSI MUMS Opening Workshop, Duke University, Durham, North Carolina, August 20–23, 2018.
7. "The GNAT method for nonlinear model reduction," Bay Area Scientific Computing Day, Lawrence Berkeley National Lab, Dec 11, 2013.

Invited

1. * "Nonlinear model reduction: Using machine learning to enable rapid simulation of extreme-scale physics models," The Peaceman Lecture on Numerical Mathematics, Rice University, Houston, Texas, October 28, 2019.
2. "Breaking Kolmogorov-width barriers in model reduction using deep convolutional autoencoders," Citrine Informatics, Redwood City, California, July 17, 2019.

3. * “Breaking Kolmogorov-width barriers in model reduction using deep convolutional autoencoders,” Physics Informed Machine Learning Workshop, University of Washington, Seattle, Washington, June 7, 2019.
4. “Nonlinear reduced-order modeling: Using machine learning to enable extreme-scale simulation for many-query problems,” Scientific Computing and Matrix Computations Seminar, University of California, Berkeley, Berkeley, California, April 17, 2019.
5. * “Nonlinear model reduction: Using machine learning to enable extreme-scale simulation for time-critical aerospace applications,” Aerospace Computational Design Laboratory, MIT, Cambridge, Massachusetts, February 22, 2019.
6. “Nonlinear model reduction: Using machine learning to enable extreme-scale simulation for many-query problems,” National Energy Research Scientific Computing Center Seminar Series, Lawrence Berkeley National Laboratory, Berkeley, California, February 15, 2019.
7. * “Nonlinear reduced-order modeling: Using machine learning to enable extreme-scale simulations in fluid dynamics,” Mechanical Engineering Department Seminar, University of Washington, Seattle, Washington, October 16, 2018.
8. “Nonlinear model reduction: Using machine learning to enable extreme-scale simulations for many-query and real time problems,” Workshop on Digital Twins and Reduced-Order Models, The Boeing Company, Bellevue, Washington, May 15, 2018.
9. “Nonlinear model reduction: Using machine learning to enable extreme-scale simulations for many-query problems,” Uncertainty Quantification Lab Seminar, Stanford University, Stanford, California, May 3, 2018.
10. * “Nonlinear model reduction: Using machine learning to enable extreme-scale simulations for many-query problems,” Workshop on Reduced Models for the Cardiovascular System, Emory University, Atlanta, Georgia, April 26–27, 2018.
11. “Nonlinear reduced-order modeling: enabling large-scale physics-based simulations for real-time and many-query problems,” Pixar Research Group Seminar Series, Pixar Animation Studios, Emeryville, California, April 24, 2018.
12. “Reduced-order modeling: using machine learning to enable large-scale simulations for many-query problems,” Advanced Modeling & Simulation Seminar Series, NASA Ames Research Center, Moffett Field, California, March 29, 2018.
13. * “Breaking computational barriers: using data to enable extreme-scale simulations for uncertainty quantification and design,” SILO Seminar Series, University of Wisconsin, Madison, Wisconsin, October 11, 2017.
14. “Using machine learning to enable extreme-scale simulations for many-query problems,” Aerospace Computing Laboratory Seminar, Stanford University, Stanford, California, August 30, 2017.
15. “Breaking computational barriers: Using data to enable extreme-scale simulations for many-query problems,” Star Talk Seminar Series, Stanford University, Stanford, California, May 22, 2017.
16. * “Model reduction for nonlinear dynamical systems: discrete optimality and adaptive refinement,” Department of Mathematics Smith Colloquium, University of Kansas, Lawrence, Kansas, May 4, 2017.
17. “Model reduction for nonlinear dynamical systems: discrete optimality and time parallelism,” Mathematical Modelling and Numerical Simulations of Biological Flows Group Seminar, INRIA, Paris, France, November 15, 2016.

18. * “Nonlinear model reduction: discrete optimality, time parallelism, and error surrogates,” Seminar in Applied Mathematics and Statistics, University of California, Santa Cruz, Santa Cruz, California, October 31, 2016.
19. * “Breaking computational barriers via nonlinear model reduction,” National Labs Day, University of California, Merced, Merced, California, October 21, 2016.
20. * “Model reduction for nonlinear dynamical systems: discrete optimality and time parallelism,” Applied and Computational Mathematics Seminar, University of South Carolina, Columbia, South Carolina, October 17, 2016.
21. * “Nonlinear model reduction: discrete optimality and time parallelism,” Absolventen-Seminar, Numerische Mathematik, Technische Universität Berlin, Berlin, Germany, July 27, 2016.
22. * “Recent advances in nonlinear model reduction,” Applied Mathematics Seminar, University of Washington, Seattle, WA, Apr 20, 2016.
23. “Nonlinear model reduction: discrete optimality and time parallelism,” Linear Algebra and Optimization Seminar, Stanford University, Stanford, CA, Nov 12, 2015.
24. “Integrating reduced-order models with uncertainty quantification: modeling and controlling error,” FRG Group Seminar, Stanford University, Stanford, CA, June 9, 2015.
25. * “Statistical modeling and adaptive control of reduced-order-model error in uncertainty quantification,” Numerical Analysis Seminar, University of Maryland, College Park, MD, March 3, 2015.
26. “Modeling and controlling reduced-order-modeling uncertainty in data assimilation,” School of Earth Sciences Seminar, Stanford University, Stanford, CA, Nov 19, 2014.
27. * “Reduced-order modeling in uncertainty quantification: modeling and controlling error,” Applied and Computational Math Seminar, George Mason University, Fairfax, VA, Apr 25, 2014.
28. * “Discrete optimality and structure preservation in nonlinear model reduction,” Applied Mathematics Seminar, University of Washington, Seattle, WA, Nov 21, 2013.
29. * “Model reduction for nonlinear fluid dynamics and structural dynamics: discrete optimality and structure preservation,” Mechanical & Aerospace Engineering Colloquium, Cornell University, Ithaca, NY, Oct 8, 2013.
30. “The GNAT method for model reduction of nonlinear dynamical systems,” Applied Mathematics Seminar, University of California, Berkeley, Berkeley, CA, Oct 2, 2013.
31. * “The GNAT method for nonlinear model reduction: discrete optimality, practical implementation, and application to CFD,” Department of Mathematics Colloquium, Virginia Tech, Blacksburg, VA, Apr 19, 2013.
32. “Discrete-optimal nonlinear model reduction by the GNAT method,” ACDL Seminar, Massachusetts Institute of Technology, Boston, MA, Apr 17, 2013.
33. “The GNAT method for nonlinear model reduction: overview and perspectives on UQ application,” Uncertainty Quantification Laboratory Seminar, Stanford University, Stanford, CA, May 3, 2012.
34. “The Gauss–Newton with approximated tensors (GNAT) method for nonlinear model reduction,” SUPRI-B Group Seminar, Stanford University, Stanford, CA, June 1, 2011.
35. “Model reduction-based iterative methods for real-time simulation and repeated analyses of mathematical models,” Linear Algebra and Optimization Seminar, Stanford University, Stanford, CA, Oct 28, 2010.

Conference (excluding proceedings)

1. "Model reduction of dynamical systems on nonlinear manifolds using deep convolutional autoencoders," 14th U.S. National Congress on Computational Mechanics, Austin, Texas, July 28—August 1, 2019.
2. "Model reduction of dynamical systems on nonlinear manifolds using deep convolutional autoencoders," Research Challenges at the interface of Machine Learning and Uncertainty Quantification, Los Angeles, CA, July 24–26, 2019.
3. "Model reduction of dynamical systems on nonlinear manifolds using deep convolutional autoencoders," 2019 SIAM Conf on Comp Sci & Eng, Spokane, WA, February 25–March 1, 2019.
4. "Conservative model reduction for finite-volume models in CFD," 13th World Congress on Computational Mechanics, New York, NY, July 22–27, 2018. *Minisymposium plenary lecture.*
5. "Machine-learning error models for quantifying the epistemic uncertainty in low-fidelity models," Research Challenges at the Interface of Machine Learning and Uncertainty Quantification, Los Angeles, CA, June 5–7, 2018.
6. "Integrating reduced-order models in Bayesian inference via stochastic error models," SIAM Conf on Uncertainty Quantification, Garden Grove, CA, April 16–April 19, 2018.
7. "Space–time least-squares Petrov–Galerkin projection for nonlinear model reduction," MoRePaS IV, Nantes, France, April 10–13, 2018.
8. "Structure-preserving model reduction for finite-volume discretizations of conservation laws," 14th U.S. National Congress on Computational Mechanics, Montréal, Quebec, Canada, July 17–20, 2017.
9. "Reducing nonlinear dynamical systems via model reduction and machine learning," USACM Workshop on Uncertainty Quantification and Data-Driven Modeling, Austin, TX, March 23–24, 2017.
10. "Structure-preserving nonlinear model reduction for finite-volume models," 2017 SIAM Conf on Comp Sci & Eng, Atlanta, GA, January 27–March 3, 2017.
11. "Structure-preserving model reduction for nonlinear finite-volume models," Workshop on Data-Driven Methods for Reduced-Order Modeling and Stochastic Partial Differential Equations, Banff International Research Station, Banff, Canada, January 29–February 2, 2017.
12. "Structure-preserving model reduction for finite-volume discretizations of conservation laws," Recent Developments in Numerical Methods for Model Reduction, Institut Henri Poincaré, Paris, France, November 7–10, 2016.
13. "Adaptive h-refinement in nonlinear model reduction: capturing moving discontinuities," 7th European Congress of Mathematics, Berlin, Germany, July 18–22, 2016.
14. "Krylov-subspace recycling via the POD-augmented conjugate gradient method," SIAM Annual Meeting, Boston, MA, July 11–15, 2016.
15. "Data-driven time parallelism and model reduction," SIAM Conf on Uncertainty Quantification, Lausanne, Switzerland, April 5–8, 2016.
16. "Applying model reduction to Krylov-subspace recycling: the POD-augmented conjugate-gradient method," 14th Copper Mountain Conf on Iterative Methods, Copper Mountain, CO, March 20–25, 2016.

17. "Discrete-optimal projection in nonlinear model reduction," 3rd International Workshop on Reduced Basis, POD and PGD Model Reduction Techniques, Cachan, France, November 4–6, 2015.
18. "Time-parallel reduced-order models via forecasting," MoRePaS III, Trieste, Italy, October 13–16, 2015.
19. "The ROMES method for statistically quantifying reduced-order model error," 13th US National Congress on Computational Mechanics, San Diego, CA, July 26–30, 2015.
20. "Discrete optimality in nonlinear model reduction: analysis and application to computational fluid dynamics," 1st Pan-American Congress on Computational Mechanics, Buenos Aires, Argentina, April 27–29, 2015.
21. "Adaptive h-refinement for reduced-order models via basis splitting," 2015 SIAM Conf on Comp Sci & Eng, Salt Lake City, UT, March 14–18, 2015.
22. "Bayesian Inference with Reduced-order Models and Statistical Error Estimates," SIAM Annual Meeting, Chicago, IL, July 7–11, 2014.
23. "Adaptive h-refinement for reduced-order models with application to uncertainty control," SIAM Conf on Uncertainty Quantification, Savannah, GA, March 31–April 3, 2014.
24. "The ROMES method for reduced-order-model uncertainty quantification: application to data assimilation," Workshop on Model Order Reduction and Data, Paris, France, Jan 6, 2014.
25. "The GNAT nonlinear model-reduction method with application to large-scale turbulent flows," Fourth International Workshop on Model Reduction in Reacting Flows (IWMRRF), San Francisco, CA, June 19–21, 2013.
26. "Preserving Lagrangian Structure in Nonlinear Model Reduction," 2013 SIAM Conf on Comp Sci & Eng, Boston, MA, February 25–March 1, 2013.
27. "A forecasting method for decreasing the temporal complexity in implicit, nonlinear model reduction," MoRePaS II, Gunzburg, Germany, October 2–5, 2012.
28. "The GNAT method for nonlinear model reduction: recent developments and application to large-scale models," 10th World Congress on Computational Mechanics, São Paulo, Brazil, July 8–13, 2012.
29. "Decreasing the temporal complexity in nonlinear model reduction," 2012 SIAM Conf on Uncertainty Quantification, Raleigh, NC, April 2–5, 2012.
30. "Efficient Model Reduction of Large-Scale Nonlinear Systems in Fluid Dynamics," 2011 SIAM Conf on Comp Sci & Eng, Reno, NV, February 28–March 4, 2011.
31. "Nonlinear model reduction using Petrov–Galerkin projection and data reconstruction," 2010 SIAM Annual Meeting, Pittsburgh, PA, July 13, 2010.
32. "A proper orthogonal decomposition-based augmented conjugate gradient algorithm for nearby problems," 2009 SIAM Annual Meeting, Denver, CO, July 7, 2009.
33. "An adaptive POD–Krylov reduced-order modeling framework for repeated analyses problems," 2009 Joint ASCE–ASME–SES Conf on Mechanics and Materials, Blacksburg, VA, June 27, 2009.
34. "A POD-based iterative solver for fast structural optimization," Seoul National University-Stanford University Student Joint Workshop, Stanford University, Stanford, CA, June 18, 2009.