Jian-Xun Wang

List of Publications by Year
in descending order

47
papers

3,647
citations

304743

22
h-index

276875

41
g-index

48
all docs

48
docs citations

48
times ranked

1760
citing authors

#	Article	IF	Citations
1	Turbulence Modeling in the Age of Data. Annual Review of Fluid Mechanics, 2019, 51, 357-377.	25.0	755
2	Surrogate modeling for fluid flows based on physics-constrained deep learning without simulation data. Computer Methods in Applied Mechanics and Engineering, 2020, 361, 112732.	6.6	408
3	Physics-informed machine learning approach for reconstructing Reynolds stress modeling discrepancies based on DNS data. Physical Review Fluids, 2017, 2, .	2.5	403
4	Physics-informed machine learning approach for augmenting turbulence models: A comprehensive framework. Physical Review Fluids, 2018, 3, .	2.5	309
5	Quantification of model uncertainty in RANS simulations: A review. Progress in Aerospace Sciences, 2019, 108, 1-31.	12.1	228
6	Quantifying and reducing model-form uncertainties in Reynolds-averaged Navierâ€“Stokes simulations: A data-driven, physics-informed Bayesian approach. Journal of Computational Physics, 2016, 324, 115-136.	3.8	209
7	PhyGeoNet: Physics-informed geometry-adaptive convolutional neural networks for solving parameterized steady-state PDEs on irregular domain. Journal of Computational Physics, 2021, 428, 110079.	3.8	201
8	Physics-constrained bayesian neural network for fluid flow reconstruction with sparse and noisy data. Theoretical and Applied Mechanics Letters, 2020, 10, 161-169.	2.8	93
9	Uncovering near-wall blood flow from sparse data with physics-informed neural networks. Physics of Fluids, 2021, 33, .	4.0	90
10	Super-resolution and denoising of fluid flow using physics-informed convolutional neural networks without high-resolution labels. Physics of Fluids, 2021, 33, 073603.	4.0	82
11	Enforcing statistical constraints in generative adversarial networks for modeling chaotic dynamical systems. Journal of Computational Physics, 2020, 406, 109209.	3.8	77
12	Flows over periodic hills of parameterized geometries: A dataset for data-driven turbulence modeling from direct simulations. Computers and Fluids, 2020, 200, 104431.	2.5	67
13	Physics-informed graph neural Galerkin networks: A unified framework for solving PDE-governed forward and inverse problems. Computer Methods in Applied Mechanics and Engineering, 2022, 390, 114502.	6.6	67
14	PhyCRNet: Physics-informed convolutional-recurrent network for solving spatiotemporal PDEs. Computer Methods in Applied Mechanics and Engineering, 2022, 389, 114399.	6.6	55
15	A Priori Assessment of Prediction Confidence for Data-Driven Turbulence Modeling. Flow, Turbulence and Combustion, 2017, 99, 25-46.	2.6	51
16	Hydro- and morpho-dynamic modeling of breaking solitary waves over a fine sand beach. Part I: Experimental study. Marine Geology, 2010, 269, 107-118.	2.1	50
17	Hydro- and morpho-dynamic modeling of breaking solitary waves over a fine sand beach. Part II: Numerical simulation. Marine Geology, 2010, 269, 119-131.	2.1	46
18	A Bayesian Calibrationâ€“Prediction Method for Reducing Model-Form Uncertainties with Application in RANS Simulations. Flow, Turbulence and Combustion, 2016, 97, 761-786.	2.6	42

#	Article	IF	Citations
19	SSR-VFD: Spatial Super-Resolution for Vector Field Data Analysis and Visualization. , 2020, , .		38
20	Prediction of Reynolds stresses in high-Mach-number turbulent boundary layers using physics-informed machine learning. Theoretical and Computational Fluid Dynamics, 2019, 33, 1-19.	2.2	33
21	A random matrix approach for quantifying model-form uncertainties in turbulence modeling. Computer Methods in Applied Mechanics and Engineering, 2017, 313, 941-965.	6.6	29
22	Non-intrusive model reduction of large-scale, nonlinear dynamical systems using deep learning. Physica D: Nonlinear Phenomena, 2020, 412, 132614.	2.8	26
23	Data-driven CFD modeling of turbulent flows through complex structures. International Journal of Heat and Fluid Flow, 2016, 62, 138-149.	2.4	25
24	Recent progress in augmenting turbulence models with physics-informed machine learning. Journal of Hydrodynamics, 2019, 31, 1153-1158.	3.2	23
25	Physics-informed deep learning for solving phonon Boltzmann transport equation with large temperature non-equilibrium. Npj Computational Materials, 2022, 8, .	8.7	23
26	Data-Augmented Modeling of Intracranial Pressure. Annals of Biomedical Engineering, 2019, 47, 714-730.	2.5	22
27	Machine Learning for Cardiovascular Biomechanics Modeling: Challenges and Beyond. Annals of Biomedical Engineering, 2022, 50, 615-627.	2.5	21
28	Learning nonlocal constitutive models with neural networks. Computer Methods in Applied Mechanics and Engineering, 2021, 384, 113927.	6.6	20
29	Assimilation of disparate data for enhanced reconstruction of turbulent mean flows. Computers and Fluids, 2021, 224, 104962.	2.5	17
30	A bi-fidelity surrogate modeling approach for uncertainty propagation in three-dimensional hemodynamic simulations. Computer Methods in Applied Mechanics and Engineering, 2020, 366, 113047.	6.6	14
31	TSUFLIND-EnKF: Inversion of tsunami flow depth and flow speed from deposits with quantified uncertainties. Marine Geology, 2018, 396, 16-25.	2.1	13
32	Beam transport modeling of PPM focused THz sheet beam TWT circuit. , 2011, , .		12
33	A Bi-fidelity ensemble kalman method for PDE-constrained inverse problems in computational mechanics. Computational Mechanics, 2021, 67, 1115-1131.	4.0	12
34	Frame-independent vector-cloud neural network for nonlocal constitutive modeling on arbitrary grids. Computer Methods in Applied Mechanics and Engineering, 2022, 388, 114211.	6.6	12
35	An Implicitly Consistent Formulation of a Dual-Mesh Hybrid LES/RANS Method. Communications in Computational Physics, 2017, 21, 570-599.	1.7	11
36	Quantification of uncertainties in turbulence modeling: A comparison of physics-based and random matrix theoretic approaches. International Journal of Heat and Fluid Flow, 2016, 62, 577-592.	2.4	10

#	ARTICLE	IF	CITATIONS
37	Physics-informed Dyna-style model-based deep reinforcement learning for dynamic control. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 2021, 477, .	2.1	10
38	Dynamic Evaluation of Mesh Resolution and Its Application in Hybrid LES/RANS Methods. Flow, Turbulence and Combustion, 2014, 93, 141-170.	2.6	9
39	INCORPORATING PRIOR KNOWLEDGE FOR QUANTIFYING AND REDUCING MODEL-FORM UNCERTAINTY IN RANS SIMULATIONS. , 2016, 6, 109-126.		9
40	Adding Constraints to Bayesian Inverse Problems. Proceedings of the AAAI Conference on Artificial Intelligence, 2019, 33, 1666-1673.	4.9	6
41	Mechanics condition of thin-walled tubular component with rib hydroforming. Transactions of Nonferrous Metals Society of China, 2012, 22, s280-s286.	4.2	5
42	Inferring tsunami flow depth and flow speed from sediment deposits based on Ensemble Kalman Filtering. Geophysical Journal International, 2018, 212, 646-658.	2.4	5
43	A semi-analytical solution and AI-based reconstruction algorithms for magnetic particle tracking. PLoS ONE, 2021, 16, e0254051.	2.5	4
44	Acoustic Inversion for Uncertainty Reduction in Reynolds-Averaged Navierâ€"Stokes-Based Jet Noise Prediction. AIAA Journal, 2022, 60, 2407-2422.	2.6	3
45	Assessment of Regularized Ensemble Kalman Method for Inversion of Turbulence Quantity Fields. AIAA Journal, 0, , 1-11.	2.6	1
46	AI-based Hybrid Model for Denoising Particle Trajectories Reconstructed from Magnetic Particle Tracking Method. , 2022, , .		0
47	A Deep-Learning Based Generalized Empirical Flow Model of Glottal Flow During Normal Phonation. Journal of Biomechanical Engineering, 2022, , .	1.3	0