

# Adam P Piotrowski

## List of Publications by Year in descending order

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Version: 2024-02-01

35  
papers

1,645  
citations

331259

21  
h-index

360668

35  
g-index

36  
all docs

36  
docs citations

36  
times ranked

1543  
citing authors

#	ARTICLE	IF	CITATIONS
1	A comparison of methods to avoid overfitting in neural networks training in the case of catchment runoff modelling. <i>Journal of Hydrology</i> , 2013, 476, 97-111.	2.3	185
2	Review of Differential Evolution population size. <i>Swarm and Evolutionary Computation</i> , 2017, 32, 1-24.	4.5	181
3	Population size in Particle Swarm Optimization. <i>Swarm and Evolutionary Computation</i> , 2020, 58, 100718.	4.5	174
4	Optimizing neural networks for river flow forecasting – Evolutionary Computation methods versus the Levenberg–Marquardt approach. <i>Journal of Hydrology</i> , 2011, 407, 12-27.	2.3	98
5	Comparing various artificial neural network types for water temperature prediction in rivers. <i>Journal of Hydrology</i> , 2015, 529, 302-315.	2.3	97
6	Adaptive Memetic Differential Evolution with Global and Local neighborhood-based mutation operators. <i>Information Sciences</i> , 2013, 241, 164-194.	4.0	95
7	Differential Evolution algorithms applied to Neural Network training suffer from stagnation. <i>Applied Soft Computing Journal</i> , 2014, 21, 382-406.	4.1	81
8	Swarm Intelligence and Evolutionary Algorithms: Performance versus speed. <i>Information Sciences</i> , 2017, 384, 34-85.	4.0	76
9	Step-by-step improvement of JADE and SHADE-based algorithms: Success or failure?. <i>Swarm and Evolutionary Computation</i> , 2018, 43, 88-108.	4.5	63
10	How novel is the ‘‘novel’’ black hole optimization approach?. <i>Information Sciences</i> , 2014, 267, 191-200.	4.0	60
11	Some metaheuristics should be simplified. <i>Information Sciences</i> , 2018, 427, 32-62.	4.0	53
12	Differential Evolution algorithm with Separated Groups for multi-dimensional optimization problems. <i>European Journal of Operational Research</i> , 2012, 216, 33-46.	3.5	52
13	L-SHADE optimization algorithms with population-wide inertia. <i>Information Sciences</i> , 2018, 468, 117-141.	4.0	52
14	Impact of deep learning-based dropout on shallow neural networks applied to stream temperature modelling. <i>Earth-Science Reviews</i> , 2020, 201, 103076.	4.0	47
15	Comparing large number of metaheuristics for artificial neural networks training to predict water temperature in a natural river. <i>Computers and Geosciences</i> , 2014, 64, 136-151.	2.0	37
16	Regarding the rankings of optimization heuristics based on artificially-constructed benchmark functions. <i>Information Sciences</i> , 2015, 297, 191-201.	4.0	35
17	River/stream water temperature forecasting using artificial intelligence models: a systematic review. <i>Acta Geophysica</i> , 2020, 68, 1433-1442.	1.0	35
18	Comparison of evolutionary computation techniques for noise injected neural network training to estimate longitudinal dispersion coefficients in rivers. <i>Expert Systems With Applications</i> , 2012, 39, 1354-1361.	4.4	34

#	ARTICLE	IF	CITATIONS
19	Simple modifications of the nonlinear regression stream temperature model for daily data. <i>Journal of Hydrology</i> , 2019, 572, 308-328.	2.3	27
20	Product-Units neural networks for catchment runoff forecasting. <i>Advances in Water Resources</i> , 2012, 49, 97-113.	1.7	24
21	Performance of the air2stream model that relates air and stream water temperatures depends on the calibration method. <i>Journal of Hydrology</i> , 2018, 561, 395-412.	2.3	24
22	Are modern metaheuristics successful in calibrating simple conceptual rainfall-runoff models?. <i>Hydrological Sciences Journal</i> , 2017, 62, 606-625.	1.2	21
23	Influence of the choice of stream temperature model on the projections of water temperature in rivers. <i>Journal of Hydrology</i> , 2021, 601, 126629.	2.3	18
24	How does the calibration method impact the performance of the air2water model for the forecasting of lake surface water temperatures?. <i>Journal of Hydrology</i> , 2021, 597, 126219.	2.3	17
25	Searching for structural bias in particle swarm optimization and differential evolution algorithms. <i>Swarm Intelligence</i> , 2016, 10, 307-353.	1.3	15
26	Relationship Between Calibration Time and Final Performance of Conceptual Rainfall-Runoff Models. <i>Water Resources Management</i> , 2019, 33, 19-37.	1.9	7
27	Evaluation of temporal concentration profiles for ungauged rivers following pollution incidents. <i>Hydrological Sciences Journal</i> , 2011, 56, 883-894.	1.2	5
28	Are Evolutionary Algorithms Effective in Calibrating Different Artificial Neural Network Types for Streamwater Temperature Prediction?. <i>Water Resources Management</i> , 2016, 30, 1217-1237.	1.9	4
29	Input dropout in product unit neural networks for stream water temperature modelling. <i>Journal of Hydrology</i> , 2021, 598, 126253.	2.3	4
30	Across Neighborhood Search algorithm: A comprehensive analysis. <i>Information Sciences</i> , 2018, 435, 334-381.	4.0	3
31	Joint Optimization of Conceptual Rainfall-Runoff Model Parameters and Weights Attributed to Meteorological Stations. <i>Water Resources Management</i> , 2019, 33, 4509-4524.	1.9	3
32	Differential evolution and particle swarm optimization against COVID-19. <i>Artificial Intelligence Review</i> , 2022, 55, 2149-2219.	9.7	3
33	Air2water model with nine parameters for lake surface temperature assessment. <i>Limnologica</i> , 2022, 94, 125967.	0.7	3
34	May the same numerical optimizer be used when searching either for the best or for the worst solution to a real-world problem?. <i>Information Sciences</i> , 2016, 373, 124-148.	4.0	2
35	On the importance of training methods and ensemble aggregation for runoff prediction by means of artificial neural networks. <i>Hydrological Sciences Journal</i> , 0, , 1-23.	1.2	2