Parameter Tuning Experiment

Supplementary material for paper: Recent Advances of the Bison Algorithm

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# 1. Goal

The goal of the experiment was to find the best parameter configuration of the Particle Swarm Optimization, the Cuckoo Search, the Bat Algorithm, and the Firefly Algorithm.

# 2. Methods

1. Find the recommended parameter configurations in the literature.
2. Run the algorithms with the recommended parameter settings on IEEE CEC 2017 benchmark in 10 and 30 dimensions, 51 runs each, each run consisting of $10000 \cdot dimension$ evaluations of the objective function.
3. Evaluate the performance of the parameter configurations for each algorithm separately. Check for statistical significance with the Wilcoxon rank-sum test and Friedman rank test.
4. Determine the most successful parameter settings, and use it in further experiments.

# 3. Test Set Definition

## *3.1 Tested Parameters*

We optimized the benchmark IEEE CEC 2017 in 10D and 30D, according to the guidelines and recommendations of this benchmark: 51 runs, each of 10 000 * dimension evaluation of the objective function. The implementations of the tested algorithms are available at *https://github.com/TBU-AILab/Bison-Algorithm*.

**Particle Swarm Optimization**

| *Source* | *NP* | $W_{max}$ | $W_{min}$ | $v_{max}$ | $C_1$ | $C_2$ | *Test set* |
|---|---|---|---|---|---|---|---|
| (Faris et al., 2016) | 50 | 0.9 | 0.2 | 6 | 2 | 2 | PSO 0 |
| (Bergh & Engelbrecht, 2006) | 50 | 0.7298 | 0.7298 | 6* | 1.49618 | 1.49618 | PSO 1 |
| (Bergh & Engelbrecht, 2006) | 20 | 0.7298 | 0.7298 | 6* | 1.49618 | 1.49618 | PSO 2 |
| (Harrison et al., 2017) | 30 | 0.5 | 0.5 | 6* | 1.9 | 1.9 | PSO 3 |
| (Maca & Pech, 2015) | 40 | 0.9 | 0.4 | 95 | 2 | 2 | PSO 4 |
| (Bergh & Engelbrecht, 2006) | 50 | 0.7298 | 0.7298 | 40[1] | 1.49618 | 1.49618 | PSO 5 |
| (Bergh & Engelbrecht, 2006) | 20 | 0.7298 | 0.7298 | 40* | 1.49618 | 1.49618 | PSO 6 |
| (Harrison et al., 2017) | 30 | 0.5 | 0.5 | 40* | 1.9 | 1.9 | PSO 7 |

**Firefly Algorithm**

| *Source* | *NP* | *Alpha* | *Gamma* | *Beta* | *Lambda* | *Test set* |
|---|---|---|---|---|---|---|
| (Faris et al., 2016) | 50 | 0.5 | 1 | 0.2 | 1.0 | FFA 0 |
| (Yang, 2008) | 50 | 0.25 | 1 | 0.2 | 1.0 | FFA 1 |
| (Yang, 2008) | 20 | 0.25 | 1 | 0.2 | 1.0 | FFA 2 |
| (Mo et al., 2013; Yang, 2010b) | 50 | 0.2 | 1.5 | 0.2 | 1.0 | FFA 3 |

**Bat Algorithm**

| *Source* | *NP* | *Loudness* | *Pulse rate* | *Alpha* | *Gamma* | $Q_{min}$ | $Q_{max}$ | *Test set* |
|---|---|---|---|---|---|---|---|---|
| (Faris et al., 2016) | 50 | 0.5 | 0.5 | | | 0 | 2 | BAT 0 |
| (Xue et al., 2015) | 50 | 0.9 | 0.9 | 0.99 | 0.9 | 0 | 5 | BAT 1 |
| (Xue et al., 2015) | 100 | 0.9 | 0.9 | 0.99 | 0.9 | 0 | 5 | BAT 2 |
| (Yang, 2010a) | 50 | 1.5 | 0.5 | | | 0 | 2 | BAT 3 |

**Cuckoo Search**

| *Source* | *NP* | $P_a$ | *Alpha* | *Test set* |
|---|---|---|---|---|
| (Faris et al., 2016) | 50 | 0.25 | 0.01 | CS 0 |
| (Yang & Deb, 2010) | 20 | 0.25 | 1 | CS 1 |
| (Yang & Deb, 2010) | 50 | 0.25 | 1 | CS 2 |
| (Faris et al., 2016) | 20 | 0.25 | 0.01 | CS 3 |

[1] Since this parameter setting was originally used on unconstrained problems, the $v_{max}$ value was not defined. However, as the IEEE CEC 2017 benchmark is bound constrained, we chose the $v_{max}$ values as follows: $v_{max}$=6 as the default value from the EvoloPy library, and $v_{max}$=40 as 20% of the search range, as recommended by (Eberhart & Yuhui Shi, 2001).

## 4. Results

**Table 1** Friedman P-values (significant if P<0.05)

| | ***PSO*** | ***FFA*** | ***BAT*** | ***CS*** |
|---|---|---|---|---|
| **10D** | 7.39E-48 | 4.99E-14 | 6.66E-11 | 7.61E-36 |
| **30D** | 1.39E-21 | 1.39E-6 | 4.12E-10 | 1.00E-29 |

### *4.1 Particle Swarm Optimization*

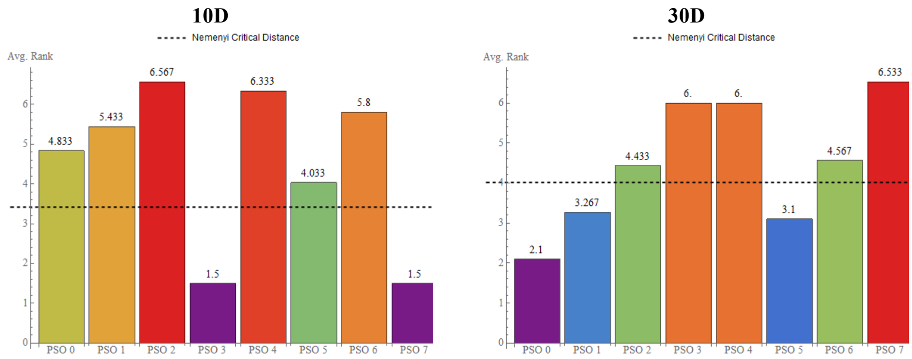


**Fig. 1** Friedman Rank Test of PSO parameter settings

**Table 2** Winning parameter settings of the PSO Algorithm with the Wilcoxon rank-sum test (α=0.05) on 30 functions of IEEE CEC 2017

| ***Dimension*** | ***PSO 0*** | ***PSO 1*** | ***PSO 2*** | ***PSO 3*** | ***PSO 4*** | ***PSO 5*** | ***PSO 6*** | ***PSO 7*** | ***None*** |
|---|---|---|---|---|---|---|---|---|---|
| 10 D | - | - | | **29** | - | | | **29** | 1 |
| 30 D | 3 | - | 2 | - | - | 5 | - | - | 20 |

*Conclusion:* The results are ambiguous.

- 10D: The best configurations are PSO 3 and PSO 7 – they both significantly outperform all the other settings in 29 cases out of 30. However, these configurations are equally successful.
- 30D:
  - PSO 0 is the most successful, according to the Friedman Rank Test.
  - PSO 5 is the most successful, according to the Wilcoxon rank-sum test.

Pair Wilcoxon Rank Sum test in Table 3 presents the results in favor of the PSO 0 configuration.

**Table 3** Wilcoxon rank-sum test on pair comparison of PSO 0 and PSO 5

| ***Dimension*** | ***PSO* 0** | ***PSO* 5** | ***None*** |
|---|---|---|---|
| 10 D | 8 | **13** | 9 |
| 30 D | **15** | 6 | 9 |

**Table 4** Wilcoxon rank-sum test on comparison of PSO 0, PSO 3 and PSO 5

| ***Dimension*** | ***PSO* 0** | ***PSO* 3** | ***PSO* 5** | ***None*** |
|---|---|---|---|---|
| 10 D | - | **29** | - | 1 |
| 30 D | 15 | - | 6 | 9 |

## *4.2 Firefly Algorithm*


**Fig. 2** Friedman Rank Test of FFA parameter settings

**Table 5** Winning parameter settings of the FFA Algorithm with the Wilcoxon rank-sum test (α=0.05) on 30 functions of IEEE CEC 2017

| ***Dimension*** | ***FFA* 0** | ***FFA* 1** | ***FFA* 2** | ***FFA* 3** | ***None*** |
|---|---|---|---|---|---|
| 10 D | 1 | - | **8** | - | 21 |
| 30 D | **13** | 1 | 3 | - | 13 |

*Conclusion:* The results are ambiguous.

- In 10D: Test sets FFA 1, and FFA 2 were better according to the Friedman rank test, and FFA 2 significantly outperformed the other settings according to the Wilcoxon Rank-Sum test.
- In 30D: FFA 0 performed significantly better.

Since IEEE CEC 2017 and 2015 benchmarks test 10, 30, 50, and 100 dimensions, we would suggest using the FFA 0 configuration.

## 4.3 Bat Algorithm

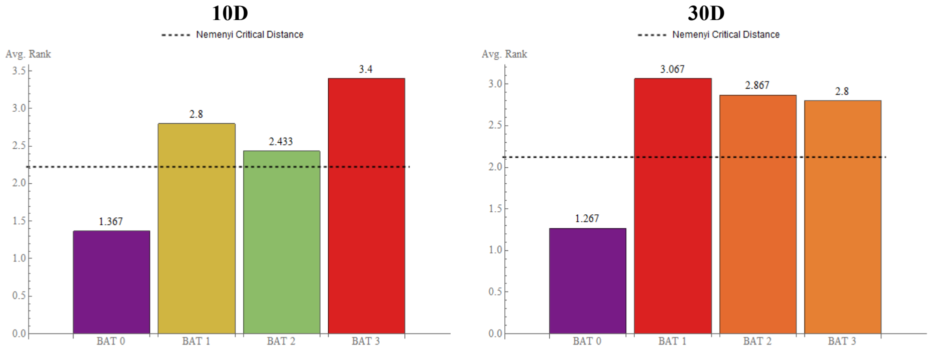


**Fig. 3** Friedman Rank Test of BAT parameter settings

**Table 6** Winning parameter settings of the Bat Algorithm with the Wilcoxon rank-sum test (α=0.05) on 30 functions of IEEE CEC 2017

| ***Dimension*** | ***BAT 0*** | ***BAT 1*** | ***BAT 2*** | ***BAT 3*** | ***None*** |
|---|---|---|---|---|---|
| 10 D | **17** | - | 1 | 2 | 10 |
| 30 D | **20** | - | - | 3 | 7 |

*Conclusion:* Test set BAT 0 is the significantly best parameter setting on the tested problems.

## 4.4 Cuckoo Search

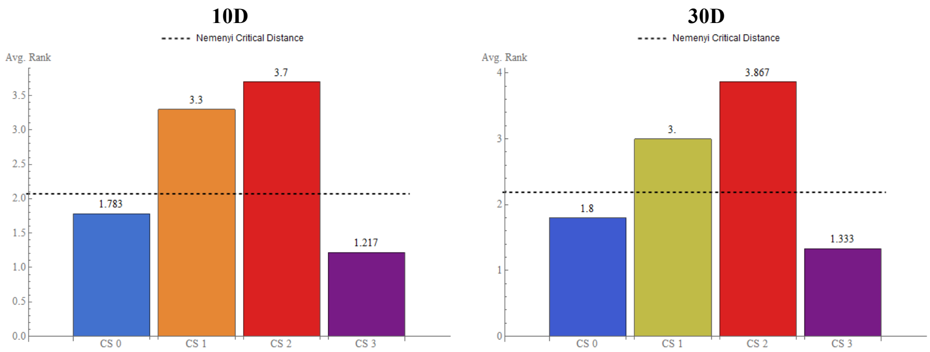


**Fig. 4** Friedman Rank Test of CS parameter settings

**Table 7** Winning parameter settings of the CS Algorithm with the Wilcoxon rank-sum test (α=0.05) on 30 functions of IEEE CEC 2017

| *Dimension* | *CS* **0** | *CS* **1** | *CS* **2** | *CS* **3** | *None* |
|---|---|---|---|---|---|
| 10 D | - | - | - | **21** | 9 |
| 30 D | 2 | 1 | - | **18** | 9 |

*Conclusion:* CS 3 is the best parameter setting according to the carried out tests.

## 5. Winning Parameter Configurations

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | ***BAT*** | | | | |
| ***Source*** | ***Pop*** | ***Loudness*** | ***Pulse rate*** | ***Alpha*** | ***Gamma*** | ***Qmin*** | ***Qmax*** | ***Test set*** |
| (Faris et al., 2016) | 50 | 0.5 | 0.5 | | | 0 | 2 | BAT 0 |
| | | | | ***FFA*** | | | | |
| **Source** | **Pop** | **Alpha** | **Gama** | **Beta** | **Lambda** | | | ***Test set*** |
| (Faris et al., 2016) | 50 | 0.5 | 1 | 0.2 | 1.0 | for D=30 | | FFA 0 |
| (Yang, 2008) | 20 | 0.25 | 1 | 0.2 | 1.0 | for D=10 | | FFA 2 |
| | | | | ***PSO*** | | | | |
| **Source** | **Pop** | $\mathbf{W_{max}}$ | $\mathbf{W_{min}}$ | $\mathbf{v_{max}}$ | **C1** | **C2** | | ***Test set*** |
| (Faris et al., 2016) | 50 | 0.9 | 0.2 | 6 | 2 | 2 | for D=30 | PSO 0 |
| (Harrison et al., 2017) | 30 | 0.5 | 0.5 | 6 | 1.9 | 1.9 | for D=10 | PSO 3 |
| | | | | ***CS*** | | | | |
| **Source** | **Pop** | **Pa** | | | ***Alpha*** | | | ***Test set*** |
| (Faris et al., 2016) | 20 | 0.25 | | | 0.01 | | | CS 3 |

## 6. References


Bergh, F. van den, & Engelbrecht, A. P. (2006). A study of particle swarm optimization particle trajectories. Inf. Sci. https://doi.org/10.1016/j.ins.2005.02.003

Eberhart, & Yuhui Shi. (2001). Particle swarm optimization: Developments, applications and resources. Proceedings of the 2001 Congress on Evolutionary Computation (IEEE Cat. No.01TH8546), 1, 81–86, 1. https://doi.org/10.1109/CEC.2001.934374

Faris, H., Aljarah, I., Mirjalili, S., Castillo, P. A., & Merelo, J. J. (2016). EvoloPy: An Open-source Nature-inspired Optimization Framework in Python: Proceedings of the 8th International Joint Conference on Computational Intelligence, 171–177. https://doi.org/10.5220/0006048201710177

Harrison, K. R., Ombuki-Berman, B. M., & Engelbrecht, A. P. (2017). Optimal parameter regions for particle swarm optimization algorithms. 2017 IEEE Congress on Evolutionary Computation (CEC), 349–356. https://doi.org/10.1109/CEC.2017.7969333

Maca, P., & Pech, P. (2015). The Inertia Weight Updating Strategies in Particle Swarm Optimisation Based on the Beta Distribution. Mathematical Problems in Engineering, 2015, 1–9. https://doi.org/10.1155/2015/790465

Mo, Y., Ma, Y., & Zheng, Q. (2013). Optimal Choice of Parameters for Firefly Algorithm. 2013 Fourth International Conference on Digital Manufacturing Automation, 887–892. https://doi.org/10.1109/ICDMA.2013.210

Xue, F., Cai, Y., Cao, Y., Cui, Z., & Li, F. (2015). Optimal parameter settings for bat algorithm. International Journal of Bio-Inspired Computation, 7(2), 125–128. https://doi.org/10.1504/IJBIC.2015.069304

Yang, X.-S. (2008). Nature-Inspired Metaheuristic Algorithms. Luniver Press.

Yang, X.-S. (2010a). A New Metaheuristic Bat-Inspired Algorithm. arXiv:1004.4170 [physics]. http://arxiv.org/abs/1004.4170

Yang, X.-S. (2010b). Firefly Algorithm, Lévy Flights and Global Optimization. In M. Bramer, R. Ellis, & M. Petridis (Ed.), Research and Development in Intelligent Systems XXVI (s. 209–218). Springer. https://doi.org/10.1007/978-1-84882-983-1_15

Yang, X.-S., & Deb, S. (2010). Engineering Optimisation by Cuckoo Search. arXiv:1005.2908 [math, stat]. http://arxiv.org/abs/1005.2908