mathematics

Editorial

Preface to the Special Issue on "Recent Advances in Swarm Intelligence Algorithms and Their Applications"—Special Issue Book

Jian Dong

School of Computer Science and Engineering, Central South University, Changsha 410075, China; dongjian@csu.edu.cn

Citation: Dong, J. Preface to the Special Issue on "Recent Advances in Swarm Intelligence Algorithms and Their Applications"—Special Issue Book. *Mathematics* **2023**, *11*, 2624. https://doi.org/10.3390/math11122624

Received: 5 June 2023
Revised: 7 June 2023
Accepted: 7 June 2023
Published: 8 June 2023

Swarm intelligence algorithms represent a rapidly growing research domain and have recently attracted a great deal of attention. They have been successfully applied in engineering, transportation, planning and scheduling, logistics and supply chains, and a broad range of other domains. They often find high-quality solutions with less computational effort than other optimization methods.

With the advancement of swarm intelligence algorithms, new variants and improvements are continuously proposed to accommodate different types of problems and application domains. The research and application of these algorithms provide an efficient and flexible approach to tackling real-world problems, while also driving the development of optimization algorithms and advancing theoretical investigations.

This Special Issue aims to highlight the latest results on swarm intelligence and its combination with real-world problems and other fields, such as engineering problems, vehicle swarm motion, viscoelastic Maxwell-type DVA, deep learning, loss of the network, echo cancellation scenarios, etc.

Contribution [1] proposes a novel discrete differential evolution (DE) algorithm to calculate the deficiency number of the tiles. In detail, to decrease the difficulty of computing the deficiency number, some pretreatment mechanisms are first put forward to convert it into a simple combinatorial optimization problem with varying variables by changing its search space. Subsequently, employing the superior framework of DE, a novel discrete DE algorithm is specially developed for the simplified problem through devising proper initialization, a mapping solution method, a repairing solution technique, a fitness evaluation approach, and mutation and crossover operations. Contribution [2] introduces chaotic mapping into the PPE algorithm to propose a new algorithm, the Chaotic-based Phasmatodea Population Evolution (CPPE) algorithm, and apply CPPE to stock prediction. The results show that the predicted curve is relatively consistent with the real curve. In [3], the viscoelastic Maxwell-type DVA model with an inverter and multiple stiffness springs is investigated with the combination of the traditional theory and an intelligent algorithm, providing a theoretical and computational basis for the optimization design of DVA. An improved multi-strategy Harris Hawks optimization (MSHHO) algorithm is proposed in paper [4]. Through experiments on 33 benchmark functions and 2 engineering application problems, it has been shown that the improved algorithm performs well in terms of optimization accuracy, convergence speed, and stability. Contribution [5] proposes a new convex combination based on grey wolf optimization and LMS algorithms, to save area and achieve high convergence speed by maximally exploiting the best features of each algorithm, presenting a customized time-multiplexing control scheme to dynamically vary the number of search agents.

An enhanced moth-flame optimization algorithm named MFO-SFR is developed to solve global optimization problems in paper [6]. The MFO-SFR algorithm introduces an effective stagnation finding and replacing (SFR) strategy to effectively maintain population diversity throughout the optimization process. The high performance of the algorithm is verified through experiments on the CEC2018 benchmark and mechanical engineering problems in the CEC2020 test-suite. In paper [7], a partition-based random search method is proposed, in which the entire feasible domain is partitioned into smaller and smaller subregions iteratively. Promising regions are partitioned faster than unpromising regions, thus exploiting promising areas earlier than unpromising areas. By cooperating with local search to refine the obtained solutions, the proposed method demonstrates good performance in many benchmark functions with multiple global optima. Aiming at the characteristics of complex networks structure and multiple design variables of energy-harvesting non-orthogonal multiple-access cognitive relay networks (EH-NOMA-CRNs), the authors of [8] utilized the proposed hybrid strategy to improve the Bat algorithm (HSIBA) to optimize the performance of EH-NOMA-CRNs. Contribution [9] formulates the cooperative attack defence evolution of large-scale agents in high-dimensional environments as a multi-population high-dimensional stochastic mean-field game (MPHD-MFG), significantly reducing the communication frequency and computational complexity, and tractably solving the MPHD-MFG with a generative-adversarial-network (GAN)-based method using the MFGs underlying variational primal-dual structure. Contribution [10] proposes a tunicate swarm algorithm based on Tent–Lévy flight (TLTSA) to avoid converging prematurely or failing to escape from a locally optimal solution. The 16 unimodal benchmark functions, 14 multimodal benchmark functions, 6 fixed-dimension functions, and 3 constrained practical problems in engineering are selected to verify the performance of the TLTSA.

The authors in [11] propose an Oppositional Pigeon-Inspired Optimizer (OPIO) algorithm to overcome the drawback of premature convergence and local stagnation. The proposed algorithm would be used to determine the load demand of a power system, by sustaining the various equality and inequality constraints, to diminish the overall generation cost. To overcome unmanned aerial vehicle swarm motion error, a near-field array beam-forming model with array element position error is constructed in [12], and the Taylor expansion of the phase difference function is used to approximately simplify the model. The improved Newton maximum entropy algorithm is proposed to estimate and compensate for the phase errors. The maximum entropy objective function is established, and the Newton iterative algorithm is used to estimate the phase error iteratively. Contribution [13] studies the cavity morphology characteristics and proposes a deep learning (DL)-based morphology classification method using 3D ground-penetrating radar (GPR) data, and experimental results are validated using the 3D GPR road modelling data obtained from the gprMax3D system. Contribution [14] provides HHO-NN (Harris Hawk Optimization-Neural network), a novel algorithm based on Harris Hawk optimization (HHO) that is capable of fast convergence when compared to previous evolutionary algorithms that automatically search for meaningful multilayered perceptron neural network (MPNN) topologies for optimal bidding. Contribution [15] presents an efficient optimization technique named the honey badger algorithm (HBA) for specifying the optimum size and location of capacitors and different types of DGs to minimize the total active power loss of the network. The combined power loss sensitivity (CPLS) factor is deployed with the HBA to accelerate the estimation process by specifying the candidate buses for optimal placement of DGs and capacitors in an RDS.

To make the Whale Optimization algorithm compatible with several challenging problems, two major modifications are proposed in [16]: the first one is opposition-based learning in the initialization phase, while the second is the inculcation of the Cauchy mutation operator in the position-updating phase. The proposed variant is named the Augmented Whale Optimization Algorithm (AWOA) and tests over two benchmark suits. Contribution [17] proposes a contextual semantic-guided entity-centric graph convolutional network (CEGCN) model that enables entity mentions to obtain semantic-guided contextual information for more accurate relational representations. This model develops a self-attention-enhanced neural network to concentrate on the importance and relevance of different words to obtain semantic-guided contextual information, employs a dependency tree with entities as global nodes, and adds virtual edges to construct an entity-centric logical adjacency matrix (ELAM). The authors in [18] introduce a new approach to enhance optimization algorithms when solving the piecewise linearization problem of a given function. Eight swarm intelligence algorithms are selected to be experimentally compared. Contribution [19] introduces a strategy to enrich swarm intelligence algorithms with the preferences of the Decision Maker (DM) represented in an ordinal classifier based on interval outranking. The hybridizing strategy is applied to two swarm intelligence algorithms, i.e., Multi-objective Grey Wolf Optimization and Indicator-based Multi-objective Ant Colony Optimization for continuous domains. The resulting hybrid algorithms are called GWO-InClass and ACO-InClass. In the survey, Contribution [20] sheds light on population-based deep reinforcement learning (PB-DRL) algorithms, their applications, and general frameworks. They introduce several independent subject areas, including naive self-play, fictitious self-play, population-play, evolution-based training methods, and the policy-space response oracle family. These methods provide a variety of approaches to solving multi-agent problems and are useful in designing robust multi-agent reinforcement learning algorithms that can handle complex real-life situations.

This Special Issue has published a total of 20 articles, comprising 19 research articles and 1 review article. The collective body of work presented herein expands the application boundaries of swarm intelligence algorithms and fosters future research in swarm intelligence and its integration with real-world problems. We find the selection of papers in this Special Issue to be highly inspiring, and we extend our gratitude to the editors and reviewers for their dedicated efforts and valuable assistance throughout this process.

Funding: This research was funded in part by the National Natural Science Foundation of China under grant number 61801521 and 61971450, in part by the Natural Science Foundation of Hunan Province under grant number 2018JJ2533, 2022JJ30052 and 2023JJ40775, and in part by the Fundamental Research Funds for the Central Universities under grant number 2018gczd014 and 20190038020050.

Conflicts of Interest: The author declares no conflict of interest.

References

1. Yan, X.; Li, Y. A Novel Discrete Differential Evolution with Varying Variables for the Deficiency Number of Mahjong Hand. *Mathematics* **2023**, *11*, 2135. [CrossRef]
2. Wu, T.-Y.; Li, H.; Chu, S.-C. CPPE: An Improved Phasmatodea Population Evolution Algorithm with Chaotic Maps. *Mathematics* **2023**, *11*, 1997. [CrossRef]
3. Chen, Y.; Li, J.; Zhu, S.; Zhao, H. Further Optimization of Maxwell-Type Dynamic Vibration Absorber with Inerter and Negative Stiffness Spring Using Particle Swarm Algorithm. *Mathematics* **2023**, *11*, 1904. [CrossRef]
4. Tian, F.; Wang, J.; Chu, F. Improved Multi-Strategy Harris Hawks Optimization and Its Application in Engineering Problems. *Mathematics* **2023**, *11*, 1525. [CrossRef]
5. Pichardo, E.; Anides, E.; Vazquez, A.; Garcia, L.; Avalos, J.G.; Sánchez, G.; Pérez, H.M.; Sánchez, J.C. A Compact and High-Performance Acoustic Echo Canceller Neural Processor Using Grey Wolf Optimizer along with Least Mean Square Algorithms. *Mathematics* **2023**, *11*, 1421. [CrossRef]
6. Nadimi-Shahraki, M.H.; Zamani, H.; Fatahi, A.; Mirjalili, S. Nadimi-Shahraki, M.H.; Zamani, H.; Fatahi, A.; Mirjalili, S. MFO-SFR: An Enhanced Moth-Flame Optimization Algorithm Using an Effective Stagnation Finding and Replacing Strategy. *Mathematics* **2023**, *11*, 862. [CrossRef]
7. Lin, Z.; Matta, A.; Du, S.; Sahin, E. A Partition-Based Random Search Method for Multimodal Optimization. *Mathematics* **2023**, *11*, 17. [CrossRef]
8. Luo, Y.; Wu, C.; Leng, Y.; Huang, N.; Mao, L.; Tang, J. Throughput Optimization for NOMA Cognitive Relay Network with RF Energy Harvesting Based on Improved Bat Algorithm. *Mathematics* **2022**, *10*, 4357. [CrossRef]
9. Wang, G.; Li, Z.; Yao, W.; Xia, S. A Multi-Population Mean-Field Game Approach for Large-Scale Agents Cooperative Attack-Defense Evolution in High-Dimensional Environments. *Mathematics* **2022**, *10*, 4075. [CrossRef]
10. Cui, Y.; Shi, R.; Dong, J. CLTSA: A Novel Tunicate Swarm Algorithm Based on Chaotic-Lévy Flight Strategy for Solving Optimization Problems. *Mathematics* **2022**, *10*, 3045. [CrossRef]
11. Ramalingam, R.; Karunanidy, D.; Alshamrani, S.S.; Rashid, M.; Mathumohan, S.; Dumka, A. CLTSA: Oppositional Pigeon-Inspired Optimizer for Solving the Non-Convex Economic Load Dispatch Problem in Power Systems. *Mathematics* **2022**, *10*, 3315. [CrossRef]

12. Zhang, Y.; Wang, G.; Leng, Y.; Yu, G.; Peng, S. IN-ME Position Error Compensation Algorithm for the Near-Field Beamforming of UAVs. *Mathematics* **2022**, *10*, 3256. [CrossRef]
13. Hou, F.; Liu, X.; Fan, X.; Guo, Y. DL-Aided Underground Cavity Morphology Recognition Based on 3D GPR Data. *Mathematics* **2022**, *10*, 2806. [CrossRef]
14. Jain, K.; Jasser, M.B.; Hamzah, M.; Saxena, A.; Mohamed, A.W. Harris Hawk Optimization-Based Deep Neural Networks Architecture for Optimal Bidding in the Electricity Market. *Mathematics* **2022**, *10*, 2094. [CrossRef]
15. Elseify, M.A.; Kamel, S.; Abdel-Mawgoud, H.; Elattar, E.E. A Novel Approach Based on Honey Badger Algorithm for Optimal Allocation of Multiple DG and Capacitor in Radial Distribution Networks Considering Power Loss Sensitivity. *Mathematics* **2022**, *10*, 2081. [CrossRef]
16. Alnowibet, K.A.; Shekhawat, S.; Saxena, A.; Sallam, K.M.; Mohamed, A.W. Development and Applications of Augmented Whale Optimization Algorithm. *Mathematics* **2022**, *10*, 2076. [CrossRef]
17. Long, J.; Liu, L.; Fei, H.; Xiang, Y.; Li, H.; Huang, W.; Yang, L. Contextual Semantic-Guided Entity-Centric GCN for Relation Extraction. *Mathematics* **2022**, *10*, 1344. [CrossRef]
18. Škorupová, N.; Raunigr, P.; Bujok, P. Usage of Selected Swarm Intelligence Algorithms for Piecewise Linearization. *Mathematics* **2022**, *10*, 808. [CrossRef]
19. Castellanos, A.; Cruz-Reyes, L.; Fernández, E.; Rivera, G.; Gomez-Santillan, C.; Rangel-Valdez, N. Hybridisation of Swarm Intelligence Algorithms with Multi-Criteria Ordinal Classification: A Strategy to Address Many-Objective Optimisation. *Mathematics* **2022**, *10*, 322. [CrossRef]
20. Long, W.; Hou, T.; Wei, X.; Yan, S.; Zhai, P.; Zhang, L. A Survey on Population-Based Deep Reinforcement Learning. *Mathematics* **2022**, *10*, 2234. [CrossRef]